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Credit Chains and Sectoral Comovement:

Does the Use of Trade Credit Amplify Sectoral Shocks?

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Abstract

This paper provides evidence of the presence and relevance of a credit-chain amplification mechanism by looking at its implications for the correlation of industries. In particular, it tests the hypothesis that an increase in the use of trade-credit along the input-output chain linking two industries results in an increase in their correlation. The analysis uses detailed data on the correlations and input-output relations of 378 manufacturing industry-pairs across 44 countries with different degrees of use of trade credit. The results provide strong support for this hypothesis and indicate that the mechanism is quantitatively relevant.

This paper—a product of the Growth and the Macroeconomics Team, Development Research Group—is part of a larger effort in the department to understand the determinants of macroeconomic volatility. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at craddatz@worldbank.org.

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1 Introduction

Trade credit is an important source of short-term financing for firms, not only in the U.S., as documented by Petersen and Rajan (1997), but also around the world. For instance, accounts payables are larger than short-term debt in 60 percent of the countries covered by Worldscope. Also, across the world most firms simultaneously receive credit from their suppliers and grant it to customers concentrated on specific industries.

These characteristics of trade credit financing have led some authors to propose it as a mechanism for the propagation and amplification of idiosyncratic shocks. The intuition is straightforward; a firm facing a default by its customers may run into liquidity problems and default to its own suppliers. Therefore, a temporary shock to the liquidity of some firms in a network that borrows from each other may cause a chain reaction in which other firms also get in financial difficulties resulting in a large and persistent decline in aggregate activity. This idea was first formalized by Kiyotaki and Moore (1997) in a partial equilibrium setting, and recently extended to a general equilibrium environment by Cardoso-Lecourtois (2004) and Boissay (2006) who have also provided evidence of the potential quantitative importance of the mechanism by calibrating their models to the cases of Mexico and the U.S.

Anecdotal evidence from surveys of firms suggests that this mechanism is relevant at the microeconomic level. Bradley and Rubach (2002) found that 31 percent of a sample of 131 firms filing for bankruptcy in the U.S. reported the non-payment by customers and businesses as the major cause for bankruptcy, and 66 percent reported that the non-payment of trade creditors had a great adverse effect on their operations. Also, based on evidence from the U.K., Chittenden and Bragg (1997) argue that firms typically respond to late payment by customers by delaying their payments to their trade creditors. However, so far there is no formal systematic empirical evidence of the presence and importance of the transmission of shocks through credit chains, which has led to some skepticism on the relevance of this mechanism at the macro level.[1] This lack of evidence is most likely the result of the absence of data sources containing the information on trade credit relations among firms required for a direct test of the hypothesis that these relations transmit and amplify shocks.

This paper partly fills this empirical gap by providing systematic evidence of the presence of the credit-chain amplification mechanism and quantifying its importance. It does so by taking an indirect approach that exploits the implications of the mechanism for the comovement of different industries and relies on widely available industry-level data. The idea behind this approach is that although the exact relations among individual firms are typically unknown, existing input-output matrices provide information on the trade relations among industries that combined with firms' balance sheets data can be used to build a measure of the use of trade credit along the chain of

[1] The reasons for this skepticism is that in some countries the amounts of net trade credit are typically small, as noticed by Coricelli and Masten (2004), which suggests the possibility that defaults may cancel out at the aggregate level if the network is circular. Basically this means that it is theoretically possible that each firm defaults on each other without affecting actual production decisions. Each firm obtains the liquidity it needs by defaulting on its suppliers

industries linking two sectors and test whether according to theory this measure explains their comovement.

I build my test using detailed data on the output of 28 manufacturing industries in a sample of 44 countries during 1980-2004 to compute the within-country correlation of the 378 resulting industry-pairs. I also gather information on the use of trade credit at the industry and country level during the same period and on input-output relations among these industries. Under some assumptions, I use these data to construct a measure of the trade credit use along the chain linking a pair of industries that approximately corresponds to a weighted average of the relative use of trade credit across all sectors linking those industries. This measure, which I label the *credit-chain distance* between two industries in a given country, is derived from an extension that introduces the possibility of credit-chain amplification in reduced form to the multi-sector model of Shea (2002).

In constructing the measure of credit-chain distance for industry pairs in different countries I make three assumptions regarding the similarity of input-output relations and relative intensity of use of trade credit across countries because of data availability problems. First, since I lack detailed input-output data for most countries in my sample, I assume that input-output linkages across industries are mostly technologically determined, so I can use data from U.S. input-output matrices to proxy for these relations in other countries. Second, in most developing counties standard data sources do not contain enough firms to build industry level measures of the use of trade credit. Thus, in most of the paper I follow the assumption of Fisman and Love (2003) that the relative use of trade credit across industries is partly technologically determined. Finally, since I do not have information on the differential use of trade credit across supplier industries, I assume that the fraction of goods that firms in a given sector buy on trade credit is similar across suppliers. I discuss these assumptions in detail in the paper, provide evidence of their validity, relax them as much as possible, and also show that they most likely result in attenuation bias that reduces the power of the tests and stacks the cards against finding any significant result.

I test my main hypothesis by running a set of regressions of the output correlation of different industry pairs across countries against the measure of *credit-chain distance* and a number of controls that include country and industry-pair fixed-effects. Consistently with the hypothesis of credit-chain amplification, I find that an increase in the use of trade credit along the chain linking two sectors, both as a fraction of the cost of inputs and relative to bank credit, significantly increases their output correlation. This result is robust to changes in the specific sample, measure of correlation, and the consideration of a set of alternative explanations.

In terms of economic magnitude, my point estimates indicate that a one-standard-deviation increase in the measure of *credit-chain distance* increases the sectoral correlation of value added of an industry pair in four percentage points, which corresponds to 16 percent of the observed standard deviation of sectoral correlations in the data (0.27). At the aggregate level, if the average country in the sample increases its ratio of accounts payables to the cost of goods sold from seven to 33 percent–a movement from the bottom to the top levels observed in the sample, the variance of its manufacturing sector will increase in about 20 percent. These magnitudes are meaningful and, moreover, the econometric procedure will tend to bias downwards the estimated coefficients, so they should be considered as lower bounds of the true economic relevance of the credit-chain amplification mechanism.

This paper contributes to several strands of literature. First and most directly, to the theoretical literature on credit-chain amplification of financial distress started by Kiyotaki and Moore (1997) and extended by Cardoso-Lecourtois (2004) and Boissay (2006). It adds to this literature by providing systematic empirical evidence of the presence and relevance of this mechanism. The paper also contributes to the finance literature on trade credit, which has mainly focused on explaining the reasons why firms use trade credit financing (see Petersen and Rajan, 1997; Burkart and Ellingsen, 2004, for good summaries) and has only recently explored the relations between trade credit use and the macroeconomy. Fisman and Love (2003) provide evidence that firms can use trade credit to substitute for formal bank financing and therefore industries where trade credit is more important can grow relatively faster in countries with weaker formal financial systems. Love et al. (2007), also provide evidence that a bank credit crunch affects the availability of liquidity in the form of trade credit by restricting the access to formal finance of firms that previously acted as financial intermediaries and provided trade credit to other firms. This paper provides evidence of an additional mechanism by which the use of trade credit itself may have macroeconomic consequences by amplifying and transmitting shocks across firms in the economy. Finally, this paper also relates to the macroeconomic literature on sectoral comovement, which has documented that business cycles are characterized by positive comovement across sectors. This has led many authors to propose mechanisms that can account for this comovement without relying on aggregate shocks. One of the proposed mechanisms is the transmission of shocks through input-output linkages (see Long and Plosser, 1983; Horvath, 2000, among others). This paper provides evidence of the relevance of this mechanism by showing that, across a large sample of countries, industries that are closer in an input-output sense are relatively more correlated.

The rest of the paper is structured as follows. Section 2 presents a stylized model of the transmission of shocks through credit chains in a multi-sector economy. Section 3 discusses the empirical implementation of the test and presents the different specifications that I estimate. Section 4 explains the manner in which the different variables included in the empirical specifications are measured and the different data sources used for this purpose. Section 5 presents the main results. Section 6 explores the robustness of these results. Section 7 concludes.

2 Theoretical Underpinnings

This section presents a simple model to illustrate the role of input-output linkages in financial contagion through credit chains. The purpose of the model is to show as simply as possible that introducing multiple intermediate goods in a stylized model of credit-chain amplification results in a relation between the use of trade credit, input-output linkages and sectoral correlations that can be tested in the data without knowing the individual links across firms in different industries. The model does not address the question of why non-financial firms extend credit to other companies. A large recent literature has explored this question in detail and proposed many mechanisms that can account for this fact (see Burkart and Ellingsen, 2004, for a recent review of the literature). Instead, I assume that, for reasons outside the model, firms sell a fraction of their goods on credit and can simultaneously access a financial intermediary to cover down payments to other firms if necessary. This coexistence of trade and bank credit has been widely documented and explained by several models such as Biais and Gollier (1997), and Burkart and Ellingsen (2004).

Time lasts two periods, $t = \{0, 1\}$. There are N sectors, each one identified with a particular intermediate good and formed by a unit mass of ex-ante identical entrepreneurs/consumers indexed by $z \in [0, 1]$ who are risk neutral, consume a final good at the end of $t = 1$, and can save at an interest rate that I assume equal to zero. At $t = 0$ all entrepreneurs in sector i are endowed with X_i units of type-i intermediate good that they can combine with the other types of intermediate goods to produce $Y_i(z)$ units of the final good at $t = 1$ using the following technology:

$$\begin{aligned} Y_i(z) =& A_i(z)(K_i(z))^{\alpha}, \\ K_i(z) =& \min\left\{\frac{X_1^i(z)}{a_1^i}, \ldots, \frac{X_N^i(z)}{a_N^i}\right\}, \end{aligned} \tag{1}$$

where z indexes the entrepreneur, $\alpha < 1$ is common for all sectors, $X_j^i(z)$ is the amount of intermediate good j used in the production of good i by entrepreneur z, and a_j^i is a technical coefficient that indicates the relative amount of good j that should be optimally used in the production of good i.[2]

Since the production of final goods requires the combination of various types of intermediates, type i entrepreneurs need to exchange part of their endowments with entrepreneurs from other sectors. To highlight the role of individual relations among entrepreneurs I assume that exchanges are personalized: entrepreneur z in sector i (henceforth z_i) gets its supply of type j intermediate good from entrepreneur z in sector j (z_j). I also assume that, for reasons outside the model, in this exchange entrepreneur z_j extends trade credit to z_i for a fraction θ_j^i of the value of the purchase expressed in units of $t = 1$ final good. Entrepreneurs do not decide how much trade credit to extend but take θ_j^i as given. Each entrepreneur has also access to funds from a bank to finance down payments if necessary, subject to a borrowing constraint. Intermediate goods markets are competitive and each entrepreneur takes the price of all intermediate goods (including hers) as given. To simplify matters even further, following Kiyotaki and Moore (1997) and Cardoso-Lecourtois (2004) I assume that there is no ex-ante uncertainty, so shocks at $t = 1$ are zero probability events and all entrepreneurs plan considering A_i as given.

Under these conditions, the problem of entrepreneur z in sector i at $t = 0$ is to select a combination of intermediate inputs to solve

[2] I use a fixed-proportions technology to highlight the input-output linkages that are the focus of the empirical section but the choice is not crucial for the derivation below.

$$
\begin{aligned}
\max_{\{X_j^i\}_{j=1}^N} \Pi_i(z) &= Y_i(z) + p_i \sum_j X_i^j(z)\theta_i^j - \sum_j \theta_j^i p_j X_j^i(z) - B_i(z) \qquad (2)\\
\text{s.t.} & \\
Y_i(z) &= A_i K_i(z)^\alpha, \\
K_i(z) &= \min\left\{ \frac{X_1^i(z)}{a_1^i}, \dots, \frac{X_N^i(z)}{a_N^i} \right\}, \\
B_i(z) &= \sum_j (1-\theta_j^i) p_j X_j^i(z) - \sum_j (1-\theta_i^j) p_i X_i^j(z), \\
B_i(z) &\leq \lambda_i p_i X_i,
\end{aligned}
$$

where p_i is the price of intermediate good i in terms of units of the final good at $t = 1$. The first term in the objective function corresponds to the value of the final good produced. The second term captures the accounts receivable of the entrepreneur, a fraction θ_i^j of the total value of the intermediate good supplied to the entrepreneur z in each sector j entrepreneurs at $t = 0$. Analogously, the third term corresponds to entrepreneur z_i's accounts payable. Finally, $B_i(z)$ is the amount borrowed (saved) at $t = 0$ to finance down-payments. The first two constraints in the maximization problem reproduce the technology available to the entrepreneur, the third is the budget constraint at $t = 0$, and the last is a borrowing constraint that restricts the amount that the entrepreneur can borrow to a fraction of her net wealth at $t = 0$. In this simple setting, an entrepreneur's demand for intermediate goods is $X_j^i = a_j^i K_i$, where K_i is adjusted according to whether the borrowing constraint binds.

If there are no shocks (and no defaults) profits will correspond to the income accrued from the production of the final good and the selling of initial endowments minus the cost of intermediate inputs, but the presence of defaults may lead profits to depart from this value. In this model a default will occur when an entrepreneur suffers a productivity shock that places its total revenue below its total debt. In this situation the entrepreneur is protected by limited liability and uses her available funds to settle debts on a pro-rata basis.

The consequences of a default will depend on whether it is caused by an idiosyncratic or a sectoral shock. If an idiosyncratic shock affects a countable number of entrepreneurs it will have affect only those entrepreneurs linked to them but will have no aggregate consequences. For instance, consider the case in which only entrepreneur z_k defaults and pays a fraction $0 \leq \mu_k(z) \leq 1$ of her debt. Because of the nature of the links among entrepreneurs, in any sector i only entrepreneur z_i's balance sheet will be directly affected by the default according to:

$$
\Pi_i(z) = Y_i(z) + p_i \sum_{j \neq k} a_i^j K_j \theta_i^j + p_i \theta_i^k a_i^k K_k \mu_k(z) - \sum_j p_j \theta_j^i a_j^i K_i - B_i. \qquad (3)
$$

Faced with this balance sheet, the entrepreneur may be forced to default on part of her its debt if $\Pi_i(z) < 0$. Otherwise, she will honor her debts and $\mu_i(z) = 1$. When $\Pi_i(z) < 0$, the pro-rata assumption implies that

$$\mu_i(z) = \frac{A(z)K_i^\alpha + p_i \sum_j \theta_i^j a_i^j K_j \mu_j(z)}{\sum_j p_j a_j^i K_i - p_i \sum_j (1-\theta_i^j) a_i^j K_j}. \tag{4}$$

Equations (3) and (4) show the standard transmission and amplification of a shock by the credit chain that has been modeled in the literature. A bad realization of $A_k(z)$ may lead entrepreneur z from sector k to default on its debt, pushing $\mu_k(z)$ below one. This reduces the profits of z entrepreneurs in all other sectors, in particular in sector i. If the impact of the decline of $\mu_k(z)$ leads z_i entrepreneurs to default, the fraction $\mu_i(z)$ they repay is increasing in $\mu_k(z)$, which further reduces the profits of entrepreneurs in sector k, and so forth. The transmission of this idiosyncratic shock is, however, confined to those firms directly linked to z_k and has no sectoral consequences. This can be easily seen from the expression for sectoral profits Π_i

$$\begin{aligned}\Pi_i &= \int_v \Pi_i(v)dv = \int_v Y_i(v)dv + p_i \sum\nolimits_j \theta_i^j a_i^j K_j \int_v \mu_j(v)dv - \int_v D_i(v)dv \\ &= \int_v Y_i(v)dv + p_i \sum\nolimits_j \theta_i^j a_i^j K_j - D_i\end{aligned}$$

where $D_i(v)$ is the total debt (payables plus bank debt) of entrepreneur v_i. The last equality indicates that aggregate profits with idiosyncratic defaults are equal to those in absence of defaults, and follows from $\mu_j(v) = 1$ almost everywhere in response to idiosyncratic shocks. This extreme result is due to the modelling individual entrepreneurs as a continuum, but captures the intuition that with a large number of firms the consequences of idiosyncratic shocks may not map into the aggregate and tracking them require knowledge of the specific linkages among firms.

The situation is different for sectoral shocks, because their consequences for other sectors can be tracked without knowing the individual links among firms. To see this, consider the case in which a fraction ϕ_k of entrepreneurs are under distress in sector k and repay a fraction μ_k of their debts. The size of this fraction is a measure of the size of the sectoral shock, and I assume without loss of generality that it corresponds to entrepreneurs $0 \leq z \leq \phi_k$. The profits of entrepreneur z_i are now

$$\Pi_i(z) = \begin{cases} Y_i(z) + p_i \sum_{j \neq k} X_i^j \theta_i^j + p_i X_i^k \theta_i^k \mu_k - D_i & \text{if } 0 \leq z \leq \phi_k, \\ Y_i(z) + p_i \sum_j X_i^j \theta_i^j - D_i & \text{if } \phi_k < z \leq 1. \end{cases}$$

The consequences of the default on sector $i's$ aggregate profits will depend on the fraction of firms affected that are also lead to default. Assuming that productivities are distributed independently of whether a firm's clients are in default, aggregate output is

$$\Pi_i = (1 - \beta(\mu_k)\phi_k)E(\Pi_i^N(z)) - \phi_k(1-\beta(\mu_k))p_i a_i^k \theta_i^k K_k (1-\mu_k),$$

where $\beta(\mu_k)$ is the fraction of the affected firms that are led to default, which depends on the size of the default μ_k, and $E(\Pi_i^N)$ denotes the expected profits with no default. Thus, the *direct* impact on sector i's profits (and consumption) Π_i of an increase in the fraction of entrepreneurs from sector

k that are in distress is

$$\frac{\partial \Pi_i}{\partial \phi_k} = -\beta(\mu_k)E(\Pi_i^N) - (1-\beta(\mu_k))p_i a_i^k \theta_i^k K_k(1-\mu_k).$$

This expression shows that, although idiosyncratic firm-level shocks affect only the individual firms linked to those that default, a sectoral shock have aggregate consequences for all those sectors that extended credit to the defaulting one. Moreover, the size of the impact will be increasing on the strength of the input-output relation a_i^k and the fraction of the purchases that were made on trade credit θ_i^k. This relation also applies to the comovement between the profits of sectors i and k because there is a direct relation between the fraction of k firms that defaults ϕ_k and sector k's aggregate profits:

$$\frac{\partial \Pi_i}{\partial \Pi_k}\frac{E(\Pi_k^N)}{E(\Pi_i^N)} = \beta(\mu_k) - \frac{(1-\beta(\mu_k))p_i a_i^k \theta_i^k K_k(1-\mu_k)}{E(\Pi_i^N)}. \tag{5}$$

This partial derivative captures only the first round effects. The total derivative will also depend on the number of sectors that are in distress as a result of the initial default, that is, on the whole credit-chain. Although the model cannot be solved in closed form, the direct effect derived in equation (5) predicts that stronger input output linkages (higher a_i^k) and a more extensive use of trade credit (larger θ_i^k) lead to a stronger comovement between sectors after one of them suffers a negative shock This is the basic prediction I test in the data.

The intuition for this result is straightforward. When an upstream supplier extends trade credit to downstream firms, it faces default risk. If there is a default, the supplier's financial health will depend on the size of the default with respect to its profits, which depends on the fraction of the total production sold to the defaulting sector (the input output linkages), and the fraction of those purchases made on credit (the use of trade credit). If some suppliers' financial health is significantly affected they may also partially default on their obligations with banks and suppliers further upstream in the credit chain, generating the credit-chain amplification previously described in the literature and captured in this model.

The model also highlights the crucial role that the use of trade credit has on the transmission of both idiosyncratic and sectoral shocks. In this model there would be no transmission if all purchases of intermediate goods were paid upfront using bank credit because banks are assumed to have deep pockets and not default, stopping the spread of the financial contagion.[3]

The model is too stylized to capture the direct demand effects transmitted through input-output linkages with perfect credit markets (see Long and Plosser, 1983). The reason is that it considers only two periods to illustrate as simply as possible the transmission of default risk in a credit chain. However, in a dynamic version of the model a decline in sector k's revenues at $t = 1$ may reduce its demand for all intermediate inputs if firms are financially constrained or if the decline comes from a persistent productivity shock as in Long and Plosser (1983). I do not focus on this aspect of transmission because it complicates the model significantly and it has been extensively analyzed

[3]The model of Kiyotaki and Moore (1997) also exhibits this property.

in the literature, but I will consider it in the empirical approach.

Summing up, this model predicts that the correlation between two sectors resulting from negative shocks will depend on the strength of their input-output linkages and the extent of use of trade credit. If the mechanism is empirically relevant, an increase in the use of trade credit should raise relatively more the correlation between sectors with stronger input output linkages. The ability of the model to explain unconditional correlations depends on the relative importance of negative and positive shocks, with the latter biasing tests of this prediction based on unconditional correlations towards zero.

3 Empirical approach

To test the empirical predictions of the stylized model outlined above I move to a simple multisectoral model based on Long and Plosser (1983) and Shea (2002) that captures the essence of the mechanism and predicts an empirical relation between a specific measure of the use of trade credit along the whole chain of sectors linking two industries and their comovement.

Consider Shea (2002)'s description of the evolution of sectoral output in a multi-sector economy without trade credit and upstream transmission of shocks through input-output linkages:

$$y_t = D\,\lambda_t, \tag{6}$$

where $y = (y_1, \dots, y_N)'$ is a vector of sectoral output fluctuations (sectors 1 to N), $\lambda = (\lambda_1, \dots, \lambda_N)'$ is a vector of sectoral shocks, and D is the DEM matrix derived by Shea (2002), whose d_{ij} element is the share of sector j in the total demand for industry i 's goods though direct and indirect linkages. This structural equation can be written in reduced form as

$$y_t = By_t + \lambda_t, \tag{7}$$

where the elements of $B = I - D^{-1}$ measure the share of the total demand for industry i's good directly attributable to sector j.

A simple modification to equation (7) introduces the possibility that the use of trade credit may affect the propagation of sectoral fluctuations. Let p_{ij} be the fraction of the direct demand b_{ij} supplied through trade credit, so that $b_{ij} = p_{ij}b_{ij} + (1 - p_{ij})b_{ij}$. If this fraction had an additional effect on the transmission of shocks, the coefficient of direct linkages would be $b_{ij}(1+\alpha p_{ij})$ instead of b_{ij}, with α parameterizing the importance of trade credit use. Further assuming for data availability reasons that p_{ij} is constant across suppliers ($p_{ij} = p_j\ \forall i$)[4] the reduced form and structural relations among sectors would correspond to

$$\begin{aligned} y_t &= B(I + \alpha P)y_t + \lambda_t, \\ &= A(\alpha, B, P)\lambda_t, \end{aligned} \tag{8}$$

[4] I discuss in detail the consequences of this assumption in section 4.1

where P is a matrix that has sector j's fraction of inputs purchased on credit (p_j) in its main diagonal, and $A = (I - B(I + \alpha P))^{-1}$ is a function of B, P, and α. If the use of trade credit does not matter for the transmission of shocks ($\alpha = 0$) this expression corresponds to the structural equation (6).

The matrix A embodies the effect of the total linkages and the credit chain. This can be seen by taking a linear approximation to A around $\alpha = 0$ to obtain

$$A \simeq D + \alpha\Gamma, \tag{9}$$

where D is the demand matrix defined above, and $\Gamma = DBPD$ captures the effect of trade credit operating through the credit-chain.

Assuming for simplicity that sectoral shocks λ_i are i.i.d, equation (8) implies that the correlation between sectors i and k is

$$\rho_{ik} = \frac{\sum_j a_{ij} a_{kj}}{\left(\sum_j a_{ij}^2 \sum_j a_{kj}^2\right)^{1/2}},$$

where a_{ij} is the (i, j) element of the A matrix defined above. This correlation depends on a complex non-linear manner on the coefficient α, but to a first order approximation it corresponds to

$$\rho_{ik} \approx \frac{\sum_j d_{ij} d_{kj}}{\left(\sum_j d_{ij}^2 \sum_j d_{kj}^2\right)^{1/2}} + \alpha \sum_j \frac{d_{ij} d_{kj} (\tilde{c}_{ij} + \tilde{c}_{kj})}{\left(\sum_l d_{il}^2 \sum_l d_{kl}^2\right)^{1/2}}, \tag{10}$$

where

$$\tilde{c}_{ij} = \frac{d_{ij}\Gamma_{ij}}{d_{ij}^2} - \frac{\sum_l d_{il}\Gamma_{il}}{\sum_l d_{il}^2}, \forall i,\, j,$$

measures the use of trade credit along the credit-chain linking i and j relative to the chains linking i and other sectors (Γ_{ij} is the i,j element of Γ).

The first term of equation (10), which I label the *input-output distance* between sectors i and k, corresponds to the correlation in absence of trade credit amplification and depends only on the strength of the linkages between these sectors, including indirect linkages through other sectors. The second term of the equation, which I label the *credit-chain distance* between industries i and k and denote by C_{ik}, is a weighted average of the relative use of trade credit across all sectors j linking these industries, where the weights are determined by the product of the direct and indirect linkages between sector j and both i and k. Intuitively, shocks to sector j will increase (decrease) the correlation between industries i and k if the use of trade credit along the chain linking j and these industries is higher (lower) than average and if the linkages between j and both industries are important.[5]

[5] The derivation above assumes for simplicity that trade credit use equally amplifies positive and negative shocks. If the trade credit mechanism is asymmetric the exact expression will be such that the term multiplying the credit chain distance will be a function of α and specific parameters of the distribution of shocks. For instance, when shocks are normally distributed with mean zero and variance σ^2 the coefficient multiplying the credit chain distance is $\alpha/2$, which means that the estimated coefficient from a regression is half the true one.

Equation (10) suggests that the hypothesis that the use of trade credit along the chain of industries linking two sectors affects the transmission of shocks (i.e. whether $\alpha = 0$ in equation (8)) can be tested by checking whether the correlation between a pair of sectors i and k depends on their credit-chain distance, C_{ik}. This test can be implemented by estimating the parameters of the following equation

$$\rho_{ikc} = \theta_c + \theta_{ik} + \alpha C_{ikc} + \beta W_{ikc} + \epsilon_{ikc}, \tag{11}$$

where θ_{ik} captures the distance effect and other fixed determinants of the correlation between a pair of industries, θ_c is a country fixed effect that captures among other things differences in the relative importance of aggregate shocks, and W_{ikc} includes other determinants of sectoral correlation. The variable of interest is C_{ikc}, the credit-chain distance between industries i and k in country c.

If shocks are independent but not identically distributed the approximation in equation (10) would contain an additional term that depends on the variances of the different sectors relative to the average, and if there is an aggregate shock the approximation would include a term that is a function of the distances and the variance of this shock. These additional terms cannot be directly computed from the data because the variances of the real shocks are unknown but I will address concerns that their presence may significantly bias the estimation of equation (11) building proxies for them that I will include in W_{ikc} in some specifications.

A similar derivation as above can be used to test the hypothesis that the use of trade credit relative to credit from intermediaries reduces the transmission of shocks, as predicted by the theory of "big pockets", by simply assuming that the fraction of purchases not financed by trade credit weaken the transmission and taking a linear approximation around a relative use of trade credit equal to zero to obtain that the coefficient of direct linkages would be $b_{ij}(1 - \alpha s_{ij})$, where s_{ij} is the ratio of formal credit to trade credit as sources of financing the purchases of inputs. The rest of the derivation is analogous changing the sign of the coefficient α, and leads to a credit chain distance measure based on the relative use of trade credit as a source of financing instead of its absolute use as derived above. Although the main discussion will focus on the measure based on the absolute use, I also build the measure based on relative use and apply it in section (5) to delve deeper into the mechanism of credit chain amplification.

In what follows I assume that the ratio of an industry's use of trade credit to the average use in a country (P_{ic}/P_c) is constant across countries, so I can express the elements of P as the product of this ratio, P_i, and a country's use of trade credit: $P_{ic} = P_i \times P_c$. This assumption, which I discuss in detail in the next section, corresponds to assuming that some industries tend to rely more on trade credit financing than other for industry-specific reasons that do not vary substantially across countries. Under these conditions, the credit-chain distance between two industries in a given country can be written as the product of their *generic credit-chain distance* and the country's typical use of trade credit $C_{ikc} = C_{ik} \times P_c$.

4 Measuring sectoral comovement, input-output linkages, and the use of trade credit

4.1 The use of trade credit

The main measure of the intensity of use of trade credit is the *Payables to Cost of Goods Sold Ratio*, P, (henceforth *Payables Financing*) which is the inverse of the payables turnover ratio widely used in financial analysis.[6] For a given firm and year it corresponds to the average of the accounts payable at the end of years t and $t-1$ divided by the total cost of goods sold in year t and measures the fraction of input purchases financed with supplier's credit.

The model presented in section 2, as well as the model of Kiyotaki and Moore (1997), suggests that the use of financial intermediaries as a source of finance for the purchase of intermediate inputs could attenuate the transmission of shocks through credit chains. To test this prediction, I also measure the relative use of intermediaries versus suppliers as sources of short-term financing by the ratio of short term debt to accounts payable, S. A high value for this ratio indicates that a firm obtains most of its short term financing from the financial system.

The empirical analysis requires representative values of these measures for various manufacturing sectors in different countries, which I obtain in the following manner (focusing on the payables financing ratio, P, to fix ideas). First, I compute a representative value of P for each country c (P_c) as the median of P across all manufacturing firms in the country with more than five years of data in Worldscope 2006, except for the U.S.where I use data from Compustat. Additionally, for the U.S. I also calculate industry-level values of P, $P_{i,US}$, aggregating all firms in a given industry in the same way described above, which then I divide by the US country-level value, P_{US}, to obtain a relative index of payables for each industry in the U.S., $P_i = P_{i,US}/P_{US}$. Industries in the U.S. where $P_{i,US}$ is higher (lower) than the overall U.S. median P_{US} will have a relative value of accounts payables P_i higher (lower) than one. Finally, assuming that these relative values for different industries are constant across countries, I estimate the industry i level value of accounts payables in a given country c, P_{ic}, as the product of the US relative value of industry i and country c 's overall median, $P_{ic} = P_i \times P_c$.

Several aspects of this procedure require further discussion. The assumption of constant relative ratios across countries is equivalent to assuming that some industries tend to rely relatively more on trade credit financing for technological reasons that do not vary substantially across countries. This assumption was previously used by Fisman and Love (2003) who also provide a series of theoretical and empirical justifications for it. My motivation for making this assumption is mainly data availability. The 2006 version of Worldscope contains data on about 10,500 manufacturing firms in 58 countries, but for most of the 36 developing countries included it does not report sufficient firms at the 3-digit ISIC industry-level. For instance, more than 40 percent of the countries in the sample have fewer than five manufacturing industries with more than five firms, and almost

[6] For a recent application of this measure to analyze the determinants of trade credit use, see Demirguc-Kunt and Maksimovic (2001).

all countries with more than 10 industries in this situation are developed countries. Nevertheless, there are three reasons to believe this assumption is unlikely to affect importantly the results. First, available evidence suggests that the relative use of trade credit across industries is to an important degree technologically determined. The ratios computed for industries with more than 20 firms in a country are significantly correlated with the ratios computed for the U.S.; the coefficient of a regression of the available country-level ratios against the US ratios results is 0.92, significant at the 1 percent level. Second, to the extent that this assumption introduces classical measurement error to the measure of the use of trade credit at the country-industry level, it will result on a downward bias on the coefficient of interest that can be substantial (see appendix). Finally, using the available data to estimate the use of trade credit at the country-industry level produces similar results to those obtained under the assumption of constant relative ratios (see section 6).

Another potentially important concern is that both data sources (Worldscope and Compustat) contain only information of publicly listed companies. If these companies' use of trade credit is different from that of the rest of the firms the estimates of the overall use of trade credit in a country will be biased. This is possible because public firms tend to be larger than private ones, and the use of trade credit is likely to depend on a firm's size. Nevertheless, as long as the variation in the use of trade credit *across countries* is mainly determined by those countries' structural characteristics the bias induced by the use of public companies will affect mainly the level of the measures but not their relative position across countries. On a more pragmatic note, to my knowledge there are no better comprehensive data sources available.

The measures of *Payables Financing* (P) and *Short Term Debt to Payables* (S) for the sample countries are presented in Table 1. The sample includes 43 countries; 22 developed, and 21 developing ones (including 3 low income). The most represented regions are Western Europe, with 15 countries, followed by East Asia and Pacific with 10, and the least represented are Sub-Saharan Africa, South Asia, and North America, with only two countries each. The main constraint to the sample is the availability of data on the use of trade credit; only for ten countries trade credit data is available but not the correlation data described below.[7] Column (3) indicates whether the measures of trade credit were built using data only from manufacturing firms (quality 1) or from the whole corporate sector (quality 2). In most cases (36 countries) there were enough manufacturing firms (10 firms) with more than five years of data to build the manufacturing specific measure, but in a few cases with less than this number non-manufacturing firms were also included in the measure. Nevertheless, all the results we discuss below carry to the subsample of high quality countries (see section 6).

Firms in the average sample country finance about 15 percent of inputs' cost with trade credit (see the mean value at the bottom of column (1)). The distribution of this ratio across countries is symmetric around this mean and there is a reasonable degree of variation that puts the 25th and 75th percentiles at 12 and 18 percent. The typical country also uses intermediary and supplier's

[7]These countries are Argentina, Brazil, Czech Republic, New Zealand, Pakistan, Russia, Switzerland, Slovakia, Slovenia, and Thailand. The main reason why these countries are excluded is that they do not count with 15 observations of the growth rate during 1980-2003 to construct the correlation matrices.

credit in relatively equal proportions (see the bottom of column (2) where the mean and median of the ratio are close to 1), but there is important degree of variation around the central tendency, with the 25th and 75th percentile values located at 0.6 and 1.6, respectively. As expected, the correlation between the two measures of trade credit use is negative but small (-0.32).

The relative measures (i.e. the ratios with respect to the mean across industries) of *Payables Financing* (P_i) and *Short Term Debt to Payables* (S_i) for the 28 ISIC industries in the U.S. are reported in Table 2. The median in column (1) is close to 1, which suggests that the distribution of *Payables Financing* across industries is relatively symmetric because the mean is one by construction. In contrast, the median in column (2) is below one, indicating that the distribution is skewed to the left. As it was with the country level variables, the degree of variation across industries is reasonable but not large. The 25th and 75th percentiles of P_i across industries correspond to 0.87 and 1.21, respectively. Again, this variation is slightly larger for S_i, with the corresponding figures at 0.71 and 1.15.

4.2 Sectoral correlations

The main measure of sectoral comovement is the correlation of the growth rates of real value added across 28 industries covering the complete manufacturing sector. The data used to build these correlations come from the United Nations Industrial Development Organization (2005), Industrial Statistics Database (henceforth UNIDO). This database contains information on nominal value added, employment, number of establishments, wages and salaries, gross output, index of industrial production, and gross capital formation for 179 countries and 28 three-digit ISIC manufacturing industries during 1963 and 2003 but the actual coverage of the data is smaller because of missing information. I use data for the period 1980-2003 so that the comovement is measured over approximately the same period where trade credit data is available, and for reasons explained below keep only those industries with at least 15 years of data during this period.

To compute the correlations, I first calculate the annual growth rates of real value added for each of the 28 industries in the different countries included in the database during 1980-2003. Following Rajan and Zingales (1998), I deflate the nominal value added of each industry in a country with the overall Producer Price Index for that country (from International Monetary Fund, 2005). Next, in each country I keep only those industries with at least 15 observations of this growth rate, and calculate their within-country, across-years correlation. To fix ideas, let g_{ict} denote the growth rate of industry i in country c between years $t-1$ and t. The estimate of the correlation between industries i and j in country c corresponds to

$$r_{ij}^{c} = \frac{\left(\sum_{t=1}^{T}(g_{ict}-\bar{g}_{ic})(g_{jct}-\bar{g}_{jc})\right)T_{ij}^{-1}}{\left(\sum_{t=1}^{T}((T_i-1)/T_i)(g_{ict}-\bar{g}_{ic})^2\sum_{t=1}^{T}((T_j-1)/T_j)(g_{jct}-\bar{g}_{jc})^2\right)^{1/2}}, \tag{12}$$

where $\bar{g}_{ic}$ is the time-average of g_{ict}, T_{ij} is the number of observations in which there are data for both sectors i, and j, and T_i is the number of observations in sector i. The reason to keep only industries with at least 15 observations for the growth rates is to avoid having a short rank correlation matrix.[8]

I compute several other measures of comovement for robustness checks. One potential problem with the baseline measure is the use of a common deflator; if there were important heterogeneity in the evolution of prices across industries, the correlations computed with a common deflator may be driven by the correlation of relative inflation rates instead of the correlation of output growth. To address this concern I also compute the correlation of the growth rates of the index of industrial production reported in UNIDO in a similar way as described above. Although results obtained using this measure should not be affected by the relative price problem, the production index data is of lower quality and smaller coverage than the value added data, so I keep the later as benchmark.[9] Nevertheless, this choice will not affect the results. Finally, I also computed the correlations of the HP filtered series of real value added and industrial production to address possible concerns regarding the de-trending procedure implicitly used when calculating the correlation in growth rates.

The average correlations across manufacturing sectors during the period for the 43 countries in the sample, as well as the number of industry pairs with data are reported in Table 3. The average correlation of real value added and industrial production growth across sectors are always positive and around 0.25 on average. The inter-quartile range situates the average correlations between 0.2 and 0.36 for value added growth and 0.22 and 0.43 for the index of industrial production. This is consistent with the extensive evidence of positive comovement across sectors during the business cycle. The summary statistics are similar for the two measures, whose averages, reported in the table, are also positively and significantly correlated (correlation of 0.39 significant at the 2 percent level). As mentioned above, the coverage is better for the measure based in value added, for which there are 13,182 industry pairs compared with 12,548 for the measure based in industrial production. Both measures of correlation are positively but not significantly correlated with the average level of GDP per capita during 1980-2000. The positive correlation may indicate that idiosyncratic sectoral shocks are relatively more important in poorer countries. I will address this issue in the empirical analysis.

Finally, Table 4 provides information on the variation of the correlation measures in the two dimensions of the data: industry-pairs and countries. The first two columns report information for the raw correlations, and the last two for the residual correlations after partialling-out country and industry-pair fixed effects. Each column (which corresponds to one measure of correlation), first reports the overall variation (as measured by the standard deviation) and its decomposition in the within– and between–countries dimensions. In columns (3) and (4) the between countries variation is zero by construction. The last two rows of each column show the average standard deviations of

[8] With N sectors and T observations, there are $N(N-1)/2$ correlation coefficients to be estimated from NT observations. The order condition, therefore, requires that $T \geq (N-1)/2$ for a full rank matrix. With 28 sectors, this requires 14 observations as a minimum. I allowed for one more than that.

[9] Yamada (2005), points out that reported indexes are in many cases not consistent over time and across industries in terms of ISIC aggregation. Also, most developing countries tend to report indexes based on the fixed weight Laspeyres formula that are not appropriate for the computation of growth rates (chain-indexes being the correct ones).

the correlation measures within industry-pair across-countries, and within-country across industry-pairs. The former is a measure of the typical variation of correlations across industry-pairs and the latter a measure of the typical variation of correlations within a country.[10] The table shows that both measures exhibit considerable variations in the within and between dimensions, although the latter is somewhat smaller than the former. The bottom two rows also show that the typical within-industry and within-country variations in correlations are similar, and, only slightly reduced by partialling-out industry-pair and country fixed effects. This indicates that an important component of the variation of the correlations is idiosyncratic (within industry-pair and country). On one hand, this is good news for the identification of the mechanism because it focuses precisely on the within-country across industry-pairs variation of the data, but on the other hand it could just mean that correlations are noisily estimated and that the standard deviation of the correlations in the sample is a demanding metric to gauge the economic relevance of the estimates.

4.3 Input-Output linkages

A central assumption of this paper is that input-output linkages between industries are largely technologically determined, based on which the linkage measures obtained in a country with good available information, like the U.S., can be extrapolated to the rest of the countries in the sample. The main reason for assuming a constant distance across industry pairs is the lack of comparable information on input-output relations for a broad set of countries at a good level of aggregation; OECD data on input-output matrices cover only 20 countries and 20 manufacturing sectors and data from Olarreaga and Nicita (2004) *Trade and protection database* covers a larger number of countries but divides manufactures in 17 sectors only and lacks some key variables required to construct the distance matrices. Nevertheless, this assumption should be relatively uncontroversial because, by construction input-output matrices reflect technological links across sectors, and, therefore, their variation across countries is likely to be limited. Table 5 and Figure 1 provide some evidence in this regard. Table 5 reports the variance decomposition of the Direct Requirement Matrices, a crucial input on the construction of the distance measures, obtained from Olarreaga and Nicita (2004) for 67 countries. Although the level of aggregation is different from the one used in this paper, the table makes apparent that almost all the variation in the direct requirement matrices is within country, across industry-pairs. Additional evidence in support of this assumption comes from Figure 1, which plots the *input-output distance* built using U.S. data as described below and the same distances estimated using U.K. data. The relation between the two measures is striking (the correlation is 0.98).

Under the assumption of technologically determined links, I build the matrix D of contempo-

[10] For any variable x_{ic} with variation across industry pairs (i) and countries (c), the within country variation corresponds to the standard deviation of $x_{ic} - \bar{x}_{.c} + \bar{x}_{..}$, where the dot represents the average in that particular dimension. The between-countries variation therefore corresponds to the standard deviation of $\bar{x}_{.c}$. The within industry-pairs, across-countries variation is computed as follows: for each industry-pair, I first calculate the standard deviation of its correlation across the countries in the sample and then compute the average of these standard deviations across all industry-pairs. I compute the within-country, across industry-pairs variation similarly by switching the order of aggregation.

raneous transmission described in section 3 (see Eq. [6]) for the 28 three-digit ISIC manufacturing industries in which I have comovement data using information from the 1992 commodity-by-industry (USE) and industry-by-commodity ($MAKE$) matrices produced by the U.S. Bureau of Economic Analysis (BEA) and my own correspondence between the BEA industry classifications and ISIC. The appendix describes the construction of this matrix in detail. Using this matrix I compute the input-output and (generic) credit-chain distances across industry pairs as described in equation (10) of section 3.

Since the sectoral classification consists of 28 industries at three-digit ISIC level, the C matrix of credit-chain distances contains 378 different distances (the distance between a sector and itself is normalized to 100). The distribution of the distances is significantly skewed with most of its mass close to zero (around 40 percent) because of the well-known sparsity of the input-output matrices (see Figure 2).[11]

Table 6 shows the twenty industry pairs with the closest *credit-chain distances*, which represent about five percent of the total number of pairs. The closest pairs are intuitive; for instance, the two pairs with the smaller distances are the ones formed by the Textiles and Wearing apparels industries and Transport Equipment and Fabricated Metal Products industries. Although pairs that are close according to *credit-chain* distance also tend to have a small *input-output* distance, there is some important degree of variation between these measures of similarity; only half of the pairs reported in Table 6 are also among the 20 with the closest input-output distance and the rank correlation between them is only 0.17. The overall correlation between both distance measures is 0.66, but is mainly driven by the difference between the group of industries with small linkages and the rest; in fact, the correlation drops to 0.5 when looking only to those industry-pairs with *input-output distances* above the median. Thus, the overall pattern suggests that the measure of *credit-chain distances* is partly determined by the input-output linkages among sectors, but the relative use of trade credit in the chain linking two sectors introduces non-trivial variation in the measure with respect to the standard input-output distance.

5 Results

This section presents the results of the test of the hypothesis that the intensity of use of trade credit along the chain linking two industries increases their correlation. Following the empirical approach outlined in section 3, I test this hypothesis by using the data to estimate the parameters of equation (11) and test whether the coefficient of the interaction of the generic credit chain distance and the use of trade credit in the country (a) is significantly positive. The coefficients obtained by ordinary least squares (OLS) for various versions of equation (11) that include different sets of additional controls are presented in Table 7. In Panel A the dependent variable is the correlation of growth rates of real value-added between industry-pairs in different countries and in Panel B is

[11] According to Horvath (1998, 2000) this sparsity is crucial to understand why the law of large numbers does not necessarily apply to models where transmission of shocks is given by input-output relations.

the correlation of growth rates of the industrial production index. The estimated coefficients for the parameter of interest are reported in the first row of the table.

The main result of the paper can be seen in the baseline regression reported in column (1), which includes only the *credit-chain distance* (i.e. the interaction of the *generic credit chain distance* C_{ik} and a country's *Payables Financing)* and a set of industry-pair and country fixed-effects. The coefficient obtained for the *credit-chain distance* based on payables is positive and strongly significant. An upstream sector that is linked to a downstream industry through a series of sectors with high use of trade credit suffers a stronger contraction as a result to a negative shock to the downstream industry. This in turn translates in a higher correlation between them.

Columns (2) and (3) of each panel show that the basic result survives the addition of variables capturing the size and the first two moments of the growth performance of the different sectors across countries. Regressions in column (2) add two measures of the size of each of the industries included in a country pair: the (log) average number of firms in each industry during the period and the industries' average share of total manufacturing value added. Adding the number of firms is important to control for the effect of diversification on sectoral correlation; assuming that there are both aggregate and idiosyncratic firm level shocks, an increase in the number of firms in all sectors of a country results in a relatively larger role for aggregate shocks and more correlated sectors. Adding the share on total manufacturing value-added of each of the industries forming an industry pair controls for the possibility of aggregate spillovers. As noticed by Shea (2002), in presence of external economies of scale, such as those suggested by Baxter and King (1991), larger industries will generate larger spillovers to the rest of the economy and therefore be more correlated with all other sectors. The results show that controlling for these variables does not affect the coefficient obtained for the main interaction. As expected, the coefficients obtained for the (log) number of firms in each of the industries are positive and significant, indicating that industries with more firms are more correlated with the rest of the economy and among themselves. Surprisingly, the coefficients obtained for the industry shares are significant but negative, but this is because the regressions are already controlling for the number of firms, which correlates with the industry share. Regressions including only the shares yield positive coefficients. Intuitively, after controlling for the number of firms, the share of an industry is a measure of value added or output per firm. The results therefore indicate that industries whose firms are relatively more productive (in the sense of having a higher level of output per firm) are typically less correlated with the rest of the economy. The regressions in column (3) further add the average and standard deviation of the corresponding growth rate of each of the industries included in a pair to control for the simple possibility that industries with similar trends or shocks can be more correlated within and across countries. The results indicate that industries that grow relatively faster and are more volatile tend to be less correlated with the rest of the sectors, but, again, adding these controls does not substantially affect the sign, magnitude, or significance of the coefficient for the credit chain distance.[12]

[12]Similar results are obtained when adding the difference in average and standard deviation between the two industries instead of adding the values for each industry separately (not reported).

Figure 3 illustrates the differential effects that the use of trade credit has across industry-pairs with different credit-chain distances. Panel A shows the relation between a country's level of payables financing and the correlation of the Iron and Steel and Transport Equipment industries (ISIC codes 371 and 384, respectively). The positive relation is apparent; for this industry pair an increase in the use of trade credit increases the correlation. Panel B instead shows the same relation for the pair formed by the Tobacco and Footwear industries (ISIC 314 and 323, respectively), which have almost no credit chain weighted linkages. The lack of association between trade credit use and correlation is also evident. These are the differences that are captured by the interaction variable. Panels C and D show that this effect is not exclusive to the pairs of industries just described. Panel C plots the relation between payables financing and sectoral correlation for the 20 industry pairs with the closest credit chain distance and panel D does the same for the 20 industry pairs with the highest distance. Again, the panels show that an increase in the use of trade credit increases the correlation of those industry pairs with a high C_{ik} but has no effect on those that are far in the credit-chain sense.[13]

In terms of economic magnitude, the point estimates (column (2)) indicate that a one-standard-deviation increase in the overall measure of *credit-chain distance* C_{ikc} results in a decline in correlation of four percentage points or 16 percent the standard deviation of industry-pair correlations within and across countries (0.27). In terms of relative differences, an increase in payable financing from the 25th to the 75th percentile level would increase the correlation of the industry pair at the 75th percentile of credit chain distance (closeness) in almost two percentage points more than that of the pair at the 25th percentile, or about ten percent of the interquartile range of average sectoral correlations (0.16). These magnitudes are economically meaningful and also likely to be conservative for several reasons. First, the appendix shows that the coefficients likely suffer from attenuation bias because of the presence of measurement error in the use of trade credit. The size of the bias will depend on the unknown variance of the measurement error, but the estimates indicate that it can be substantial. For instance, for a standard deviation of the error equal to the standard deviation of *Payables Financing* across countries the bias may be as large as 60 percent. Second, as explained in section 2, the credit-chain amplification mechanism is mainly associated with increases in the correlation across industries resulting from the impact of negative shocks. Therefore, using the unconditional correlation as dependent variable will also lead to attenuation bias because there is an important component of the observed correlations that the model does not explain. Third, the measures of correlations most likely contain an important amount of noise resulting from the small number of observations used in their estimation. Finally, as shown in Table 4 and briefly discussed above, the measured correlations of growth in value-added and the index of industrial production across industry-pairs and countries exhibit a considerable amount of variation even after accounting for country- and industry-specific components, which makes difficult for any individual mechanism to account for a large fraction of the residual variability.

The aggregate implications of the mechanism can also be estimated by computing the impact on

[13] The results reported in the figure are robust to excluding Italy (ITA) from the sample.

aggregate volatility of an increase in a country's overall use of trade credit implied by the coefficients. This can be easily done by noticing that a country's aggregate manufacturing variance (σ_Y^2) can be written as

$$\sigma_Y^2 = \omega' \Omega^{\frac{1}{2}} R \, \Omega^{\frac{1}{2}} \omega,$$

where ω is a vector containing the share of each manufacturing sector on total manufacturing value added, Ω is a matrix that has the variance of each manufacturing sector in the diagonal (and zero elsewhere), and R is the correlation matrix between the different manufacturing sectors, such that $R_{i,j} = \rho_{i,j}$. Thus, extrapolating from equation (11)

$$\frac{\partial \sigma_Y^2}{\partial P} = \alpha \omega' \Omega^{\frac{1}{2}} \tilde{C} \, \Omega^{\frac{1}{2}} \omega,$$

where $\tilde{C}$ is the matrix of generic credit-chain distances, and the partial derivative indicates that the expression corresponds to the impact of trade-credit use through changes in correlations only. Evaluating this expression for a country with the average sectoral shares and variances yields that an increase in the aggregate level of *Payables Financing* from the 25^{th} to the 75^{th} percentile level (from 12 to 18 percent) reduces the variance of value-added growth in the manufacturing sector of the average country by five percent. A bigger increase from the lowest to the highest level accounts payables in the sample (from 7 to 33) reduces this variance in 20 percent.[14] Moreover, as discussed above, these magnitudes are likely to be a lower bound of the true effect on aggregate variance. Overall, the evidence suggests that the credit-chain amplification mechanism is quantitatively relevant.

Using the *Short Term Debt to Payables* ratio of the different industries and countries to compute the *credit-chain distance* C_{ikc}, a different albeit complementary measure of the use of trade credit, yields similar results. This can be seen in columns (1) to (3) of both panels of Table 8. Since this is an inverse measure of the use of trade credit, the credit chain mechanism predicts a negative coefficient for the main variable (see the discussion in section 3). Consistently, in all the regressions the coefficient is negative and strongly significant; an increase in the relative importance of bank credit vis-à-vis supplier's credit along the credit chain reduces the transmission of shocks. This is consistent with Kiyotaki and Moore (1997)'s idea that it is the presence of "big pockets" along the chain that can dampen the transmission of shocks. The economic magnitude of the coefficient associated with this measure of trade credit use is smaller than that obtained when using payables financing. A one standard deviation increase in the credit chain distance based on this measure reduces the correlation of real value added growth in two percentage points; half of the reduction obtained with the baseline measure.

Despite its smaller magnitude, the attenuation of sectoral comovement resulting from an increase in the use of formal financing is mostly complementary to the one resulting from an overall decrease in the use of trade credit, as shown in columns (4) to (6) of both panels of Table 8. The regressions reported in this table include both measures of credit-chain distance simultaneously and show that

[14] Seven and 25 percent of the inter-quartile range of variance of aggregate manufacturing value added growth.

the coefficients associated with the measure based on payables financing decline only slightly with respect to those previously reported and the coefficients associated with the short term debt to payables are mostly unaffected. This indicates that both the use of trade credit relative to other sources of short term financing and as a fraction of input purchases are important for amplification. A reduction in the use of trade credit as a fraction of the cost of inputs that is compensated with an increase in the use of intermediary financing has a much larger impact on reducing sectoral comovement. Evaluated at the median level short term debt to payables, the same increase in payable financing from the 25th to the 75th percentile discussed above would increase the correlation of the industry pair at the 75th percentile of credit chain distance in almost 2.5 percentage points more than that of the pair at the 25th percentile; this is fifty percent larger than the direct effect without changing the use of short term debt, and about 15 percent of the interquartile range of average sectoral correlations.

6 Robustness

This section explores the robustness of the main result to variations in the sample of countries and industry-pairs included, the use of different measures of correlation and credit chain distance, and alternative explanations associated with potential omitted variables.

6.1 Sample issues

A first concern regarding the baseline results is that they may be driven by special observations. This concern is valid considering the skewness of the distribution of the measures of credit-chain distances and trade credit use, but it turns out to be unimportant. First, no individual country or industry pair is driving the results. This can be seen in the results summarized in both panels of Figure 4. Panel A reports the distribution of the 43 coefficients for the credit-chain distance obtained after re-estimating the baseline regression dropping one country at a time. All coefficients are positive, statistically significant at the one percent level, and tightly distributed around the median coefficient of 1.98, with the smallest coefficient (1.36) obtained when Japan is excluded from the sample. The histogram presented in Panel B addresses the robustness to the exclusion of specific industry pairs in a similar manner; all the 378 coefficients, are significant and similar to the coefficient of the baseline regression. Second, no particular groups of observations are driving the findings. The regressions presented in Table 9 check for various of these possibilities. Column (1) reports the results obtained using only the sample of 39 "high quality" countries where the use of trade credit of the manufacturing sector could be computed. Column (2) presents results obtained after dropping the ten percent of countries with the highest and lowest levels of *Payables Financing* (i.e. dropping 20 percent of the sample in total). Column (3) shows similar results after dropping the 5 percent of industry pairs with the highest and lowest generic credit chain distances (10 percent of sample), and Column (4) reports the results obtained using a robust estimation method. In all cases and in both panels the coefficient of the *credit-chain distance* is not importantly affected.

6.2 Measurement

The regressions reported so far have used the correlation in the growth rates of real value added and industrial production index as measures of comovement. The exercises presented in Table 10 consider three alternatives. Column (1) addresses potential concerns with the use of first differences as a de-trending procedure and reports the coefficients obtained when using as dependent variable the correlation of the series of real value added de-trended using the Hodrik-Prescott filter. Column (2) uses a transformation of the correlation of the growth rate of real value added aimed to tackle the potential heteroskedasticity of the residuals resulting from the correlations taking values between -1 and 1. The transformed correlations are $\tilde{r}^c_{ik} = \ln(r^c_{ik} + 1) - \ln(1 - r^c_{ik})$, which assumes a parametric non-linear relation between the correlations r^c_{ik} and the variables of the model (see Otto et al., 2001, who introduced this). In both cases, the coefficient for the *credit-chain distance* is negatively significant. Finally, Column (3) addresses concerns about the impact of outliers in the measures of correlations by replacing the standard measure described in equation (12) by a robust measure. The results are again largely unaffected.[15]

The last two regressions presented in Table 10 check the robustness of the results to changes in the measure of credit chain distance. Column (4) reports the results obtained after relaxing as much as possible the assumption of fixed relative use of trade credit across industries that introduced in section 4.1 and using the available country-specific measures of sectoral use of trade credit that can be obtained from Worldscope. The measure of credit chain distance applied in this column uses the country-industry value of payables financing, P_{ic}, measured directly from Worldscope for all country-industries with data on more than five firms (395 cases in the sample), and the product of the U.S. relative and the corresponding country median ($P_{ic} = P_{i,US} \times P_c$) in the remaining cases (1305 cases). The results show that using as much country level information as possible does not affect the main conclusion of the paper; the coefficient obtained for the credit chain distance is similar to that previously reported. Column (5) explores the sensitivity of the main coefficient to the particular choice of the U.S. as baseline country for measuring the input-output relations across industries and uses instead *credit-chain distances* computed using input-output matrices from the U.K. The rest of the procedure to construct the distance is the same as in the baseline case. Again, the coefficient is of the right sign and significance and are only marginally smaller.

6.3 Are industries with small credit chain distances similar in other dimensions?

Industries that are closer in terms of credit-chain distance may also be similar in other dimensions such as technologies, degrees of external financial requirements, liquidity needs, capital intensity, and stage of production. To the extent that these other dimensions of similarity are emphasized by country characteristics related to the use of trade credit, the results could be spuriously related to the omission of these potential determinants of comovement. The regressions presented in Table 11 explore several of these possibilities.

[15]The specific measure is the weighed correlation between two industries, where the weights are obtained from a robust regression between the two growth rate series.

The measure of credit chain distance could be capturing technological similarities across industries that buy (sell) comparable proportions of goods from (to) other industries, shown by Conley and Dupor (2003) to be related to the comovement of productivity in the US. To check this concern I add the interaction of the measures of BUY and $SELL$ distances between industries of Conley and Dupor (2003) and a country's payables financing to the baseline specification.[16] The main coefficient is not importantly affected and the results indicate that only industries that sell goods to similar sectors in similar proportions are significantly more correlated in countries with higher payables financing. This suggests that a higher use of trade credit increases the relevance of backward linkages as sources of comovement, consistently with the upward transmission of shocks emphasized by the credit-chain mechanism.

Industries with high degrees of external financial requirements or liquidity needs may respond more to shocks in countries with underdeveloped financial systems. Since a country's use of trade credit may be related to the availability of formal financing associated with financial development it is necessary to control for this potential source of comovement. The degree of financial development of a country can also be related to the availability of capital, which can induce comovement across industries with similar capital intensities. All these possibilities are considered in the regression reported in column (2) that adds to the baseline specification the interaction of an industry-pair's similarity in terms of external financing requirements (measured as in Rajan and Zingales, 1998) and liquidity needs (measured as in Raddatz, 2006) and a country's level of financial development, and the product of an industry-pair's similarity in terms of capital intensity (measured as in Raddatz, 2006) and a country's (log) aggregate capital per worker. Along each dimension, the degree of similarity is computed as the absolute value of the difference between each industry's measure. The degree of financial development is measured as the (log) average private credit to GDP ratio during 1980-2000 from **?**, and capital per-worker is the average for the same period from **?**(henceforth PWT). The results show that only industries with similar liquidity needs are less correlated in financially developed countries, suggesting that the increased access to financing eases the response of industries with high liquidity needs to negative shocks and reduces the resulting correlation,[17] but this channel does not importantly affect the coefficient associated with credit chain distance.

Sectors producing goods with similar degrees of complexity can also be relatively more correlated. For instance, Clark (1999) and Huang (2001) have documented that the response of quantities versus prices in response to a monetary policy shock vary with the stage of production. Therefore, sectors at comparable stages of production will exhibit more coordinated responses in quantities than sectors at different stages. I use the Gini coefficient of the distribution of input costs to capture the complexity/stage of production of the goods produced by an industry (see Blanchard and Kremer, 1997; Kremer, 1993) and measure the similarity of two industries in this dimension

[16] Let $\Phi(i, j)$ be the dollar value of compensation to sector i for goods used in industry j obtained directly from the input output tables. An industry's fraction of the costs and demand of other sector are obtained by normalizing the Φ matrix across rows and columns to obtain $B(i,j) = \Phi(i,j)/\sum_k \Phi(k,j)$ and $\Psi(i,j) = \Phi(i,j)/\sum_k \Phi(i,k)$. The BUY and $SELL$ distances correspond to the Euclidean distance of the vectors of costs and demand shares between two industries and correspond to $BUY(i,j) = \left[\sum_k (B(k,i) - B(k,j))^2\right]^{\frac{1}{2}}$ and $SELL(i,j) = \left[\sum_k (\Psi(i,k) - \Psi(j,k))^2\right]^{\frac{1}{2}}$.

[17] For the relation between liquidity needs and vulnerability to financial underdevelopment see Raddatz (2006).

as the absolute value of the difference in their Gini coefficients (obtained from Cowan and Neut, 2002). The regression presented in column (3) adds to the main specification the interaction of this variable with the overall volatility of a country measured by the standard deviation of the growth rate of real GDP per capita. Although, consistently with this mechanism, sectors producing goods of similar complexity are indeed more correlated in more volatile countries, the result regarding the role of credit-chains remains unaltered.

The credit-chain mechanism emphasized throughout the paper focuses mainly on the transmission of shocks through backward linkages but forward linkages may also be important, not only for technological reasons (productivity shocks upstream translating into an increase in production downstream because of an expansion of the supply of intermediates) but also for credit reasons because an upstream shock could affect the supply of trade credit for downstream industries. The regressions presented in columns (4) to (6) check for this possibility. Column (4) starts by adding the interaction between the input-output distance between two industries derived from the $COST$ matrix of transmission of upstream shocks described in Shea (2002) and a country's payables financing to check if the main result could be simply related to upstream transmission being more important in countries with higher use of trade credit.[18] The results suggest that industries with stronger forward linkages tend to co-move more in countries with higher payables financing, but this channel does not importantly affect the findings regarding the role of credit chain distance. The regressions reported in columns (5) and (6) go one step forward and ask whether the forward linkages may matter in the transmission of credit default. The regression in column (5) adds to the baseline specification a measure analogous to the credit chain distance built using the $COST$ matrix (instead of D) and payables financing to check for the possibility that upstream shocks affect relatively more downstream industries that rely more on trade credit. The regression in column (6) instead focuses on the constraints to the supply of credit and adds a measure of distance built using the $COST$ matrix and the upstream industry's level of accounts receivables to sales as a measure of the amount of credit offered to downstream industries. The results indicate that only the measure based on the use of credit downstream is related to the degree of comovement in countries with higher aggregate use of trade credit, which suggest that upstream shocks benefit relatively more downstream industries that use relatively more trade credit, but do not provide evidence consistent with contractions on trade credit supply.

The derivation of equation (10) assumed that sectoral shocks were independent and identically distributed. Relaxing this assumption would result in additional terms on the linear approximation that will also be a function of the elements of the D matrix, raising, therefore, the possibility that the credit chain distance could be picking the effect of one of these omitted variables. One possible deviation from this assumption comes from differences in the variance of the shocks across industries. In this case, the linear approximation (10) would include a term that is a function of the coefficients of the D matrix and the relative variances of the sectoral shocks. This term

[18]The input-output distance based in this matrix is computed analogously to the distance based on the D matrix (see Eq. [10])

cannot be directly computed because these variances are unobserved, so the regression in column (7) adds a proxy built using the relative variances of the output of the various industries instead. Although imperfect, this measure should properly capture the correlation coming from the input-output linkages, which is the source of concern. The results clearly indicate that this concern is not relevant for the main findings. Another possibility is the presence of aggregate shocks. In the model of section 3, sectoral shocks result in aggregate fluctuations because of the input-output linkages, therefore, aggregate shocks are not necessary to generate comovement. Nevertheless, the presence of truly aggregate shocks will also add a term to the linear approximation that will depend on the input-output linkages and the variance of the aggregate shock, but whose exact form will depend on specific assumptions regarding the transmission of this shock. For this reason, the regression in column (8) controls for this potential source of bias in a general manner by adding the interaction of a country's overall volatility and the generic credit chain distance, which maximizes the potential correlation with the component of the transmission of aggregate shocks that is a function of input-output linkages.

6.4 Alternative explanations and further evidence on the mechanism

Since the measure of credit chain distance was constructed using U.S. data, one possible interpretation of the findings is that they are simply indicating that input-output linkages can better explain sectoral comovement in countries that are similar to the U.S. This is unlikely because the U.S. is not atypical in its level of trade credit use (payables financing in the U.S. is 0.13, just below the sample median of 0.14). Nevertheless, I check for this possibility by adding to the baseline specification the interaction of the generic credit-chain distance and the (log) average real GDP per capita (from PWT) during 1980-2000. The results, reported in column (1) of Table 12, show that consistently with the measurement hypothesis linkages are more important in developed countries, but this does not significantly affect the findings regarding credit chains and sectoral comovement. Column (2) shows similar results when also controlling for a country's overall degree of volatility (as measured by the standard deviation of the growth rate of real value added during 1980-2003).

The results obtained using the ratio of short term debt to payables (see Table 8) indicate that the actual use of formal financing from financial intermediaries vis-a-vis suppliers credit partly alleviates the transmission of shocks through credit chains. Building on these results, column (3) checks whether the availability of formal financing affects the importance of the credit-chain mechanism by allowing the parameter α to depend on a country's degree of financial development, which amounts to add a triple interaction term. Surprisingly, the results indicate that the credit chain mechanism is stronger in more financially developed countries.[19] A possible interpretation of this finding is that financial development also increases the supply of trade credit, at least in this sample, which would be consistent with Demirguc-Kunt and Maksimovic (2001) who maintain that these sources of financing are complements. If this is the case, increasing the availability of formal

[19]This finding is robust to controlling for the simple interaction between financial development and GDP per capita and generic credit chain distance.

credit does not necessarily reduce the importance of trade credit in the actual composition of firm's financing. To check whether the actual composition matters, the regression in column (4) instead allows the parameter α to depend on the country level ratio of short term debt to payables and finds that the use of formal financing reduces the importance of the credit-chain mechanism.

A firm that sells its intermediate goods to downstream producers in a foreign country is probably not affected by shocks to *local* downstream producers. This observation suggests that the relevance of the credit chain mechanism may depend on a country's degree of trade openness. The exercise presented in column (5), which includes the interaction between an industry pair's generic credit chain distance and a country's degree of trade openness (measured as the log ratio of exports plus imports to GDP), shows that indeed input-output linkages are less important in more open countries but that this finding is not behind the main result of the paper. This result is robust to controlling for the overall level of development (not reported).

The credit chain distance between two sectors can be decomposed in various forms that shed light on the mechanism and the sources of identification. First, the regression reported in column (6) determines the relative importance of direct and indirect linkages (first and higher round effects in the transmission of shocks) by computing the credit chain distance resulting from first round effects only and adding it to the baseline specification. [20]The results show a higher and statistically significant coefficient for the distance based on first round effects than for the overall distance, which suggests that the marginal impact of these linkages on sectoral correlations is higher. However, their overall contribution to the differences in correlation is smaller because although their coefficient is almost four times larger than that of the overall distance, their sample variation is an order of magnitude smaller. Indirect linkages are, therefore, qualitatively and quantitatively important for the mechanism. Second, the regression in column (7) disentangles the contribution to sectoral correlations of differences in the use of trade credit across industries from the contribution of their average use. The credit chain distance in equation (10) can be trivially written as the distance when all industries use the average level of trade credit plus the contribution of the industries' deviations from that average. These two components (that add to the credit chain distance) are separately included in the regression in column (8). The results show that it is the average use of trade credit along the chain of industries linking two sectors that is behind the result of this paper. The differences across industries do not contribute significantly and, if anything, tend to reduce the correlation. The lack of significance is not surprising considering the limited variation of the relative use across industries compared to the variation in input-output linkages, and the negative sign seems to indicate that industries with stronger linkages with the rest of the economy tend to use relatively less trade credit.

[20]Iterating on the reduced form equation (7) yields the recursive representation of equation (8), $y = (\tilde{B} + \widetilde{B}^2 + \tilde{B}^3 + \ldots + \tilde{B}^N)\lambda + \tilde{B}^{N+1}y$, which shows that the structural form corresponds to the sum of the first, second, and higher order rounds of effects of the shocks. The first order effect is given by $\widetilde{B}\lambda$ and the resulting correlation matrix is derived as in section 3.

7 Concluding remarks

This paper has provided indirect evidence of the presence and quantitative importance of the credit-chain amplification mechanism first described in Kiyotaki and Moore (1997) by looking at its implications for the comovement of industries within and across countries. The results, which exploit the variation in correlations of industry-pairs and use of trade credit across countries, robustly indicate that, consistently with the presence of a credit-chain amplification mechanism, an increase in the intensity of use of trade credit along the input-output chain linking two industries augments the correlation between them.

In terms of economic significance, the evidence indicates that, without being a first order determinant of comovement and volatility, the credit-chain amplification mechanism is quantitatively relevant. Moreover, there are several reasons to consider the estimates as conservative.

In addition to the possible causes of attenuation already discussed in the paper, there are at least three other dimensions that deserve to be considered in future work. First, one possible cause of the limited variation in the measures of distances across industry pairs is the level of aggregation used in this paper. At a lower level of aggregation, it may be possible to capture more of the local interactions between similar industries that is now part of the "diagonal" terms of the distance matrices. The reason for not working at a lower level of aggregation in this paper is the exponential increase in the number of observations in the time dimension that are required to satisfy the order condition in the computation of the correlation matrices, but this restriction may become less important as the time coverage of existing datasets increases. Second, the data used in this paper do not include the non-manufacturing sectors, such as retailing, the main users of trade credit and likely a major contributor to credit chain amplification. Finding ways of including these sectors is likely to be relevant to quantify the real importance of this mechanism. Finally, for data availability reasons and to avoid endogeneity problems, this paper's analysis focused on the unconditional correlations, despite that according to theory the credit-chain amplification mechanism affects mainly the comovement resulting from negative shocks. As discussed in the paper, the presence of this asymmetry is likely to weaken the tests and bias downwards the estimates of the relevance of the mechanism. Addressing some of the issues should form part of future research in this area.

Appendix

A Building the Ultimate Demand Requirements Matrix D

Following Shea (1990, 2002) I build the D matrix for the 28 three-digit ISIC industries using information from the 1992 commodity-by-industry (USE) and industry-by-commodity ($MAKE$) matrices produced by the US bureau of economic analysis (BEA) and my own correspondence between the industry classification used by the BEA and ISIC . The first step in the construction of this matrix is the computation of the *Direct Cost Share Matrix* (DCS) whose i, j element is the amount of industry i input required per dollar of industry j's output. I compute this matrix directly from the U.S. benchmark input-output matrices by multiplying the $MAKE$ and USE matrices to obtain each industry's use (in dollars) of goods produced by other industries, dividing each column by the total value of the output produced by that particular industry to obtain the *Direct Requirement Matrix*(DRQ), and then correcting this matrix for the presence of non-zero terms in the diagonal resulting from aggregation according to

$$DCS = (I - diag(DRQ))^{-1}(DRQ - diag(DRQ))$$

where the $diag()$ operator extracts the main diagonal of a matrix. Next I compute the $COST$ matrix, whose i, j element is the ultimate dollar requirement of good j per dollar sold of good i, by calculating the transpose of the Leontieff inverse of the DCS matrix $(I - DCS')^{-1}$, and extracting the 28 rows and columns corresponding to the ISIC manufacturing industries. Finally, I calculate the *Ultimate Demand Requirement Matrix* (D) as

$$D_{ik} = COST_{ki}a_k / \left(\sum_{z=1}^{N} COST_{zi}a_z \right),$$

or, in matrix notation,

$$D = diag(COST\ Diag(a))^{-1} COST\ Diag(a)$$

where a_k is the steady state share of good k in overall consumption, $a = (a_1, ..., a_N)$ and the $Diag()$ operator takes a vector and places it in the main diagonal of a matrix. I compute the industry k's final demand following in Shea (2002) as the sum of purchases from consumption, government, and other non-manufacturing industries. The matrix for the U.K. used in the robustness section was built in the same manner.

B Measurement error

B.1 Errors in the measurement of sectoral use of trade credit

I now describe the impact that the presence of classical measurement error in the sectoral use of trade credit on the estimated coefficient for credit chain distance. According to equation (9) in the paper, $A \approx D + \alpha C$ to a first order approximation, where $C = DBPD$. Consider the case of classical measurement error in the diagonal matrix P of sectoral use of trade credit

$$P = \tilde{P} + \varepsilon,$$

where ε is a matrix that contains in the diagonal the error terms in the measure of trade credit use of the different sectors and zero elsewhere and $\tilde{P}$ is the matrix of true sectoral use. Assume that, according with standard measurement error, the matrix ε is such that

$$E[\tilde{p}_i \varepsilon_j] = 0, \;\; \forall i, \, j \quad \in 1, .., N. \tag{13}$$

Under these assumptions the true matrix $\tilde{C}$ can be written as

$$\begin{aligned} \tilde{C} =& DB(P - \varepsilon)D \\ =& C - \mu. \end{aligned}$$

It is easy to verify that under assumption (13) the components of $\tilde{C}$ and (linear combinations of $\tilde{p}$ and ϵ, respectively) are orthogonal, so that μ corresponds to standard measurement error for the C matrix.

On the other hand, the correlation matrix of sectoral output correspond to

$$\rho = diag(AA')^{\frac{-1}{2}} AA' diag(AA')^{\frac{-1}{2}}, \tag{14}$$

where $A = (I - B(I - \alpha P))^{-1}$, and, to a first order approximation around $\alpha = 0$

$$\rho = \left. \rho(\alpha) \right|_{\alpha=0} + \left. \frac{d\rho(\alpha)}{d\alpha} \right|_{\alpha=0}.$$

After some simple but tedious algebra, this approximation can be written as

$$\begin{aligned} \rho(\alpha) \approx & \, diag(DD')^{\frac{-1}{2}} DD' \, diag(DD')^{\frac{-1}{2}} - diag(DD')^{\frac{-1}{2}} DD' \, diag(DD')^{\frac{-3}{2}} diag\left(\tilde{C}D'\right) + \\ & diag(DD')^{\frac{-1}{2}} \left(\tilde{C}D' + D\tilde{C}'\right) diag(DD')^{\frac{-1}{2}} - diag(DD')^{\frac{-3}{2}} diag(\tilde{C}D') DD' \, diag(DD')^{\frac{-1}{2}}, \end{aligned}$$

which is the matrix form of equation (10) in the paper. This expression clearly shows that the first order approximation of the correlation matrix is linear in the true matrix $\tilde{C}$, and, therefore, as a function of α and C can be written as

$$\rho(\alpha, C) = \rho(\alpha, \tilde{C}) + \rho(\alpha, \mu),$$

where it is still true that the first term on the RHS is a linear combination of the elements of $\tilde{P}$ and the second term is a linear combination of the elements of μ. Therefore, under assumption (13), the second term corresponds to classical measurement error associated with the first term, which attenuates the estimated coefficient for α.

Using a similar derivation is possible to show that deviations from the assumption of a firm's constant relative use of trade credit across suppliers ($p_{ij} = p_j$) introduce no bias in the estimated coefficients to a first order approximation. I skip the details for reasons of space, but the argument relies on the matrix A being equal to $(I - B(I + \alpha P) - \alpha\tilde{B})^{-1}$, where under classical measurement error the matrix $\tilde{B}$ (the element by element product of the matrix D and the random deviations from the common usage effect) is orthogonal to P. This implies that to a first order approximation the correlation matrix ρ equals the one obtained under the common usage assumption $\rho(\alpha, \tilde{C})$ plus an orthogonal term.

Although the derivation above shows that to a first order approximation measurement error in the sectoral use of trade credit translates into measurement error in the distances, one might still be concerned that the non-linearity of the true relation between correlations and the matrix of sectoral use could change the bias. In other words, one might be concerned about the quality of the first order approximation. To address this concern I performed a series of Montecarlo simulations to explore empirically the direction of the bias introduced by the measurement error.

I perform these simulations in the following manner. First, I take my current estimates of the sectoral use of trade credit, measured as *Payables Financing* as the true values ($\tilde{P}$) and generate a series of "observed" values (P) by adding some noise to the current estimates. I try different magnitudes for the size of this noise around the baseline level corresponding to the standard deviation of the observed values of payables financing across industries and countries. I then assume a value of 2 for α (as in the baseline regression) compute the true A matrix as $A = (I - B(I - \alpha\tilde{P}))^{-1}$, and use this matrix to compute simulated correlations among industries within countries according to equation (14). Next, I compute the *credit-chain distance* measure as described in the paper using the simulated values of P and run a regression between the simulated correlations and *credit-chain distances* for the various industries in the sample of fictitious countries, which has the same size as the actual sample, controlling for industry-pair and country fixed effects. I repeated this exercise 100 times for each value of the standard deviation of the noise between 0.01 and 0.16 (the standard deviation of P in the sample is 0.08).

The results are summarized in Figure A1 (Panel A), which, for each value of the standard deviation of the errors shows the empirical distribution of the difference between the simulated and true coefficients. The continuous line correspond to the mean of this distribution and the shaded area is the 95 percent empirical confidence interval. The x-axis display the corresponding standard deviations of the measurement error as a fraction of the sample standard deviation of P. The figure clearly shows that the introduction of noise in the measure of the sectoral use of trade credit results in attenuation bias and that the size of the bias increases with the magnitude of the measurement error (as captured by its standard deviation). It also suggests that the attenuation bias may be quantitatively important, reaching about 60 percent for a standard deviation equal to the observed variation of payables financing across countries and industries.

B.2 Impact of the use of a common measure of Input-Output distances

The main body of the paper presented some evidence indicating that input-output linkages among industries are mainly technologically determined and, therefore, that extrapolation of the distance measures built using U.S. data to other countries is unlikely to result in significant biases. Here I formally examine this statement by performing a series of Montecarlo simulations to explore the potential biases arising from making this assumption in a setting analogous to the one used in the paper.

The simulations are performed as follows. I first compute a fictitious true D matrix for each country in the sample as the sum of the D matrix computed for the U.S. plus some random noise. Notice that the D matrices are such that their columns add to one, and typically have large values in the diagonal (mean value is 0.78) because most the final demand for a product is typically embodied in final purchases of the product itself.[21] I, therefore, introduce noise in a manner that is roughly consistent with these characteristics by first re-scaling the matrix such that its rows add to 100, adding to each element a small error derived from a uniform distribution with positive domain between zero and a varying number set between 0.5 and 2, and then re-normalizing the rows. In this way I preserve the heavy-diagonal property of the simulated matrices but at the same time introduce significant noise.[22]

After generating the simulated true matrices, I consider country 1 as the benchmark country and pick the matrix simulated for it as the baseline measure, which I impute to all other countries. With the true distances, the actual measures of trade credit use, and a value of the parameter α of 2 I simulate the correlations according to equation (14), and with the imputed common distance compute the *credit-chain distances* between industries in different countries as described in the paper. I then run a regression between the simulated correlations and *credit-chain distances* in the fictitious sample. I do this 100 times for each value of the upper limit of the uniform distribution between 0.5 and 2. The results of the simulation are summarized in the Panel B of Figure A1. The figure is in the same scale as the one in Panel A to facilitate the comparison of the magnitude of the different biases, and shows that the assumption of a common matrix also biases the estimated coefficient downwards, but the size of the bias is small, never exceeding 10 percent. The bias slightly increases with the size of the error, but this is unnoticeable using this scale.

[21] This is a standard characteristic of input-output matrices that should hold across countries.

[22] For instance, when drawing noise from a uniform distribution between zero and one, the expected value of the draw is 0.5. Considering that there are 27 other sectors, the expected sum of the noise across these sectors is about 14. So, even in the extreme case in which the share of the diagonal was 1, this share is expected to fall to 0.88 after introducing the noise. Proceeding in this way likely introduces more noise than what would be observed in real data.

Overall, the Montecarlo experiments confirm the intuition that the bias introduced by the assumption of a common distance across countries goes in the right direction (attenuation) and is probably small.

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Table 1. Trade credit use in sample countries

Country	Payables Financing	Short Term Debt to Payables	Quality Trade Credit Data
	(1)	(2)	(3)
Australia	0.13	0.24	1
Austria	0.11	1.60	1
Belgium	0.15	0.91	1
Canada	0.19	0.25	1
Chile	0.11	1.86	1
China	0.20	2.73	1
Colombia	0.07	2.45	1
Denmark	0.10	1.00	1
Egypt	0.18	3.04	2
Spain	0.20	0.79	1
Finland	0.10	1.20	1
France	0.17	0.55	1
United Kingdom	0.16	0.42	1
Greece	0.14	1.78	1
Hong Kong, China	0.15	1.21	1
Hungary	0.13	0.87	1
Indonesia	0.12	3.26	1
India	0.17	0.89	1
Ireland	0.15	0.56	1
Iceland	0.15	1.85	2
Israel	0.18	0.58	1
Italy	0.33	0.81	1
Jordan	0.13	1.26	2
Japan	0.24	0.76	1
Korea	0.13	2.15	1
Sri Lanka	0.08	3.09	2
Morocco	0.21	0.27	2
Mexico	0.14	1.12	1
Malaysia	0.12	1.94	1
Netherlands	0.12	0.61	1
Norway	0.10	0.31	1
Peru	0.11	2.36	1
Philippines	0.18	1.29	1
Poland	0.14	0.78	1
Portugal	0.12	1.53	1
Singapore	0.15	0.82	1
Sweden	0.11	0.31	1
Turkey	0.13	1.10	1
Taiwan, China	0.12	1.98	1
United States	0.13	0.40	1
Venezuela, RB	0.20	1.25	2
South Africa	0.19	0.21	1
Zimbabwe	0.08	0.92	2
Mean	0.15	1.24	--
Median	0.14	1.00	--
St. Dev.	0.05	0.83	--
Percentile 25	0.12	0.59	--
Percentile 75	0.18	1.82	--

Payables Financing is the ratio of accounts payables to the cost of goods sold; *Short term debt to Payables* is the ratio of short term debt to accounts payables. The figures reported for each country correspond to the median level of each ratio across all manufacturing firms in the country, except for the countries where quality equals 2 (column (3)), where it corresponds to the ratio across all firms. For each firm, each measure is the median across the years with data during the period 1980 to 2005. Only firms with more than 5 years of data are included in the computation of the country median and only countries with more than 10 of these firms are included in the sample.

Table 2. Relative use of Trade credit across U.S. manufacturing industries

ISIC code	Industry	Relative Payables Financing (1)	Relative Short Term Debt to Payables (2)
311	Food products	0.82	1.01
313	Beverages	1.37	0.55
314	Tobacco	0.92	0.92
321	Textiles	0.93	0.94
322	Wearing apparel, except footwear	0.93	1.92
323	Leather products	0.69	2.10
324	Footwear, except rubber or plastic	0.73	1.27
331	Wood products, except furniture	0.62	1.16
332	Furniture, except metal	0.77	0.75
341	Paper and products	0.86	0.57
342	Printing and publishing	0.95	0.87
351	Industrial chemicals	1.23	0.56
352	Other chemicals	1.51	0.58
353	Petroleum refineries	1.27	0.43
354	Misc. petroleum and coal products	1.02	0.97
355	Rubber products	0.87	0.85
356	Plastic products	1.01	0.72
361	Pottery, china, earthenware	0.58	0.88
362	Glass and products	0.94	1.35
369	Other non-metallic mineral products	1.06	0.67
371	Iron and steel	0.94	0.70
372	Non-ferrous metals	0.95	1.18
381	Fabricated metal products	0.97	1.15
382	Machinery, except electrical	1.32	0.80
383	Machinery, electric	1.27	1.03
384	Transport equipment	0.90	0.78
385	Professional & scientific equipment	1.36	0.90
390	Other manufactured products	1.20	2.00
	Median	0.95	0.89
	Percentile 25	0.87	0.71
	Percentile 75	1.21	1.15
	Correlations		
	Relative Inv. Payables Turnover	1	
	Relative Short Term Debt to Payables	-0.32	1

Column (1) reports the ratio of accounts payable to cost of goods sold in a given manufacturing industry in the U.S. to the overall U.S. mean in manufactures. Similar ratios are reported for short-term debt to payables (column (2)). The values of each measure for a given industry correspond to the median across all U.S. firms in that industry included in Compustat during 1980-1989. The value for the U.S. manufacturing sector as a whole corresponds to the median across industries. For a given firm, the ratios correspond to their median across the years in which the firm reported data.

Table 3. Average correlations and number of observations in sample countries

Country	Average corr. of VA growth	No. ind. pairs with VA growth	Average corr. of IIP growth	No. ind. Pairs with IIP growth	Average GDP Per capita 1980-2000
	(1)	(2)	(3)	(3)	(4)
Australia	0.22	190	0.35	190	20,483
Austria	0.13	378	0.23	378	19,220
Belgium	0.07	91	0.15	231	19,290
Canada	0.17	378	0.46	378	21,974
Chile	0.26	378	0.36	378	6,861
China	0.48	231	--	--	2,133
Colombia	0.15	378	0.29	378	4,897
Denmark	0.29	378	0.23	378	21,853
Egypt	0.03	378	0.14	378	3,226
Spain	0.23	351	0.25	351	14,062
Finland	0.13	378	0.30	378	18,726
France	0.77	325	0.23	325	19,028
United Kingdom	0.32	378	0.54	378	17,888
Greece	0.20	210	0.00	210	12,185
Hong Kong, China	--	--	0.49	322	20,416
Hungary	0.69	325	0.57	351	9,093
Indonesia	0.20	276	0.20	276	2,889
India	0.14	378	0.11	378	1,705
Ireland	0.11	325	0.27	325	14,819
Iceland	0.06	231	--	--	20,625
Israel	0.11	253	0.36	231	14,005
Italy	0.40	325	0.22	377	18,505
Jordan	0.05	325	0.09	120	3,962
Japan	0.31	378	0.39	378	20,773
Korea	0.38	378	0.46	378	10,010
Sri Lanka	0.32	325	--	--	2,564
Morocco	0.03	66	0.07	136	3,418
Mexico	0.10	325	0.65	325	7,587
Malaysia	0.16	378	0.19	325	7,001
Netherlands	0.28	276	0.16	275	19,206
Norway	0.14	325	0.17	377	21,372
Peru	0.31	378	0.60	378	4,404
Philippines	0.29	378	0.12	378	3,075
Poland	0.53	45	0.65	215	7,001
Portugal	0.17	351	0.17	378	11,815
Singapore	0.24	276	0.22	276	16,627
Sweden	0.49	378	0.21	378	19,878
Turkey	0.15	378	0.23	378	5,630
Taiwan, China	0.29	378	0.26	378	10,732
United States	0.41	378	0.43	378	26,235
Venezuela, RB	0.31	378	--	--	7,090
South Africa	0.26	253	0.39	253	7,645
Zimbabwe	0.15	300	0.29	253	2,721
Mean	0.25	314	0.30	322	12,154
Median	0.22	338	0.25	377	11,815
St. Dev.	0.17	88	0.16	75	7,347
Percentile 25	0.14	276	0.18	276	5,264
Percentile 75	0.31	378	0.39	378	19,213

Column (1) reports the average correlation of value added growth among industry pairs (excluding the correlation between an industry and itself). Column (2) displays the number of non-repeated industry pairs in which we have data on the correlation of value added growth per country (a given industry pair is counted only once). Columns (3) and (4) present similar information for the correlation of the growth of the industrial production index. Column (5) shows the average real GDP per capita of each country during the period 1980-2000.

Table 4. Analysis of Variance of Correlation Measures

	Panel A: Raw data		Panel B: Partialling out country and industry pairs FE	
	Correlation of growth rate of real value added (1)	Correlation of growth rate of index of industrial produciton (2)	Correlation of growth rate of real value added (3)	Correlation of growth rate of index of industrial produciton (4)
Overall	0.33	0.33	0.27	0.25
Between countries	0.16	0.17	--	--
Within countries	0.29	0.28	0.27	0.25
Within industry-pair across countries	0.29	0.28	0.27	0.27
Within country across industry pairs	0.29	0.28	0.27	0.27

The table reports various summary statistics of the variation of the correlation of the growth or real value added (columns (1) and (3)) and index of industrial production (columns (2) and (4)) across industry pairs along several dimensions. Panel A presents information for the raw measures of correlation, and Panel B reports indicators for the residual correlations after partialling-out country and industry pair fixed effects. The row labeled *Overall* reports the overall standard deviation of each variable across countries and industry pairs. *Between countries* and *Within countries* report the standard deviation of the correlation measures along these two dimensions. The last two rows of each column report the average within industry-pair across-countries, and within-country across industry-pairs standard deviations of the correlation measures. The within-industry across countries variation is computed taking, for each industry-pair, the standard deviation of its measured correlations across the countries in the sample, and then calculating the average of these standard deviations across all industry-pairs. The within-country, across industry pairs variation is computed similarly by switching the order of aggregation

Table 5. Analysis of Variance of Measures of Direct Requirements

	Direct Requirements
Overall	0.026
Between countries	0.004
Within countries	0.026
Within industry-pair across countries	0.007
Within country across industry pairs	0.024

The table reports various summary statistics of the variation of the components of the matrices of direct requirements across industry pairs and countries along several dimensions. The row labeled *Overall* reports the overall standard deviation of the measures across countries and industry pairs. *Between countries* and *Within countries* report their standard deviation along these two dimensions. The last two rows report the average within industry-pair across-countries, and within-country across industry-pairs standard deviations of the direct requirement measures. The within-industry across countries variation is computed taking, for each industry-pair, the standard deviation of its direct requirement measures across the countries in the sample, and then calculating the average of these standard deviations across all industry-pairs. The within-country, across industry pairs variation is computed similarly by switching the order of aggregation

Table 6. Industry pairs with the smallest Credit-Chain Distances

ISIC code industry 1	Industry 1	ISIC code industry 2	Industry 2	Credit chain Distance	Ranking
321	Textiles	322	Wearing apparel, except footwear	90.67	1
381	Fabricated metal products	384	Transport equipment	63.17	2
351	Industrial chemicals	352	Other chemicals	63.06	3
356	Plastic products	384	Transport equipment	61.31	4
351	Industrial chemicals	384	Transport equipment	60.15	5
362	Glass and products	384	Transport equipment	59.47	6
356	Plastic products	372	Non-ferrous metals	54.15	7
351	Industrial chemicals	372	Non-ferrous metals	53.30	8
323	Leather products	324	Footwear, except rubber or plastic	49.27	9
362	Glass and products	372	Non-ferrous metals	49.11	10
356	Plastic products	371	Iron and steel	48.90	11
351	Industrial chemicals	371	Iron and steel	47.18	12
355	Rubber products	384	Transport equipment	46.95	13
351	Industrial chemicals	356	Plastic products	44.69	14
341	Paper and products	342	Printing and publishing	43.77	15
362	Glass and products	371	Iron and steel	42.99	16
356	Plastic products	383	Machinery, electric	40.30	17
355	Rubber products	372	Non-ferrous metals	39.77	18
362	Glass and products	383	Machinery, electric	39.28	19
371	Iron and steel	384	Transport equipment	39.24	20

The table shows the input-output distances of the twenty industry pairs with the smallest (generic) credit-chain distances computed using the 1992 U.S. input-output matrices. The first four columns of the table describe the names and ISIC codes of the industries that comprise each pair. The column labeled *Credit-Output Distance* displays the estimated value of the distance. This measure is such that a higher value implies a smaller distance. The last column indicates the ranking in terms of closeness of each industry pair across the whole set of 378 possible pairs.

Table 7. Credit chains and sectoral correlations

	Panel A: Dependent variable is the correlation of real value added growth			Panel B: Dependent variable is the correlation of growth in industrial production index		
	(1)	(2)	(3)	(1)	(2)	(3)
Credit Chain Distance (Payables Financing) (α)	1.978***	2.058***	1.927***	1.455***	1.504***	1.481***
	(0.327)	(0.327)	(0.327)	(0.357)	(0.372)	(0.371)
(log) Number of establishments industry 1	--	0.024***	0.019***	--	0.037***	0.036***
		(0.004)	(0.004)		(0.004)	(0.004)
(log) Number of establishments industry 2	--	0.024***	0.022***	--	0.011**	0.012**
		(0.004)	(0.004)		(0.005)	(0.005)
Share of total manufacturing VA industry 1	--	-0.239**	-0.305***	--	-0.243**	-0.301**
		(0.098)	(0.098)		(0.114)	(0.118)
Share of total manufacturing VA industry 2	--	-0.669***	-0.672***	--	-0.149	-0.089
		(0.104)	(0.105)		(0.112)	(0.115)
Average growth industry 1	--	--	-0.131*	--	--	-0.426***
			(0.073)			(0.109)
Average growth industry 2	--	--	-0.004	--	--	-0.713***
			(0.074)			(0.093)
Standard deviation growth industry 1	--	--	-0.205***	--	--	-0.337***
			(0.027)			(0.074)
Standard deviation growth industry 2	--	--	-0.102***	--	--	-0.237***
			(0.022)			(0.057)
Observations	13182	12683	12683	12548	11146	11146
R-squared	0.34	0.35	0.35	0.41	0.40	0.41
Industry pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Credit chain distance (Payables Financing) is the measures of the intensity of use of trade credit in the chain linking two industries based on the *Payable Financing* ratio. *(log) Number of establishments industry 1 (2)* is the log of the average number of firms in the first (second) industry in the corresponding industry pair. *Share of total manufacturing VA industry 1 (2)* is the average share of the first (second) industry pair on total manufacturing value added. *Average growth industry (1)* is the average growth of real value added (Panel A) and index of industrial production (Panel B) in the first (second) industry in the pair. *Standard deviation growth industry 1 (2))* is the standard deviation of the growth of real value added (Panel A) and index of industrial production (Panel B) in the first (second) industry in the pair. All averages mentioned above are computed over the period 1980-2000. All regressions include country and industry pair fixed effects. Standard errors are robust to heteroskedasticity. * = Significant at 10 percent level, ** = Significant at 5 percent level, *** = Significant at 1 percent level.

Table 8. Credit chains, relative use of formal financing and sectoral correlations

Panel A: Dependent variable is the correlation of real value added growth

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Chain Distance (Short term debt to payables)	-0.097***	-0.092***	-0.099***	-0.072***	-0.065***	-0.075***
	(0.021)	(0.021)	(0.023)	(0.022)	(0.022)	(0.024)
Credit Chain Distance (Payables Financing)	--	--	--	1.676***	1.798***	1.627***
				(0.344)	(0.343)	(0.347)
(log) Number of establishments industry 1	--	0.023***	0.018***	--	0.023***	0.018***
		(0.004)	(0.004)		(0.004)	(0.004)
(log) Number of establishments industry 2	--	0.024***	0.021***	--	0.024***	0.021***
		(0.004)	(0.004)		(0.004)	(0.004)
Share of total manufacturing VA industry 1	--	-0.224**	-0.295***	--	-0.245**	-0.314***
		(0.098)	(0.098)		(0.098)	(0.098)
Share of total manufacturing VA industry 2	--	-0.667***	-0.675***	--	-0.684***	-0.690***
		(0.105)	(0.105)		(0.104)	(0.105)
Average growth industry 1	--	--	-0.141*	--	--	-0.130*
			(0.073)			(0.073)
Average growth industry 2	--	--	0.001	--	--	-0.001
			(0.073)			(0.073)
Standard deviation growth industry 1	--	--	-0.212***	--	--	-0.208***
			(0.027)			(0.027)
Standard deviation growth industry 2	--	--	-0.103***	--	--	-0.102***
			(0.022)			(0.022)
Observations	13182	12683	12683	13182	12683	12683
R-squared	0.34	0.35	0.35	0.34	0.35	0.35

Panel B: Dependent variable is the correlation of growth in industrial production index

	(1)	(2)	(3)	(4)	(5)	(6)
Credit Chain Distance (Short term debt to payables)	-0.066***	-0.071***	-0.070***	-0.045*	-0.050*	-0.050*
	(0.026)	(0.027)	(0.026)	(0.027)	(0.029)	(0.028)
Credit Chain Distance (Payables Financing)	--	--	--	1.275***	1.316***	1.293***
				(0.382)	(0.395)	(0.393)
(log) Number of establishments industry 1	--	0.036***	0.036***	--	0.037***	0.036***
		(0.004)	(0.004)		(0.004)	(0.004)
(log) Number of establishments industry 2	--	0.010**	0.011**	--	0.011**	0.012**
		(0.005)	(0.005)		(0.005)	(0.005)
Share of total manufacturing VA industry 1	--	-0.225**	-0.282**	--	-0.245**	-0.303***
		(0.114)	(0.117)		(0.114)	(0.118)
Share of total manufacturing VA industry 2	--	-0.147	-0.087	--	-0.163	-0.101
		(0.112)	(0.115)		(0.112)	(0.115)
Average growth industry 1	--	--	-0.443***	--	--	-0.429***
			(0.109)			(0.109)
Average growth industry 2	--	--	-0.711***	--	--	-0.714***
			(0.093)			(0.093)
Standard deviation growth industry 1	--	--	-0.338***	--	--	-0.339***
			(0.074)			(0.074)
Standard deviation growth industry 2	--	--	-0.234***	--	--	-0.233***
			(0.057)			(0.057)
Observations	12548	11146	11146	12548	11146	11146
R-squared	0.41	0.40	0.41	0.41	0.40	0.41

Credit chain distance (Payables Financing) is the measures of the intensity of use of trade credit in the chain linking two industries based on the *Payable Financing* ratio. *Credit chain distance (Short term debt to payables)* is the intensity of use of trade credit in the chain linking two industries based on the *Short-term debt to payables* ratio. *(log) Number of establishments industry 1 (2)* is the log of the average number of firms in the first (second) industry in the corresponding industry pair. *Share of total manufacturing VA industry 1 (2)* is the average share of the first (second) industry pair on total manufacturing value added. *Average growth industry (1)* is the average growth of real value added (Panel A) and index of industrial production (Panel B) in the first (second) industry in the pair. *Standard deviation growth industry 1 (2))* is the standard deviation of the growth of real value added (Panel A) and index of industrial production (Panel B) in the first (second) industry in the pair. All averages mentioned above are computed over the period 1980-2000. All regressions include country and industry pair fixed effects. Standard errors are robust to heteroskedasticity. * = Significant at 10 percent level, ** = Significant at 5 percent level, *** = Significant at 1 percent level.

Table 9. Variations in the sample

	High Quality sample (1)	Dropping extreme Trade Credit (2)	Dropping Extreme distances (3)	Robust Estimation (4)
Credit Chain Distance (Payables Financing)(α)	2.323***	1.846***	2.952***	1.895***
	(0.340)	(0.660)	(0.561)	(0.373)
(log) Number of establishments industry 1	0.026***	0.020***	0.025***	0.024***
	(0.004)	(0.005)	(0.004)	(0.004)
(log) Number of establishments industry 2	0.020***	0.019***	0.024***	0.027***
	(0.005)	(0.005)	(0.005)	(0.004)
Share of total manufacturing VA industry 1	-0.330***	-0.442***	-0.313***	-0.255***
	(0.123)	(0.111)	(0.103)	(0.095)
Share of total manufacturing VA industry 2	-0.696***	-0.772***	-0.699***	-0.720***
	(0.116)	(0.113)	(0.108)	(0.102)
Constant	-0.074	-0.026	-0.091**	-0.296***
	(0.047)	(0.046)	(0.044)	(0.074)
Observations	10680	9804	11431	12683
R-squared	0.36	0.37	0.35	0.35
Industry pair FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Credit chain distance is the measures of the intensity of use of trade credit in the chain linking two industries based on the *Payable Financing* ratio. *(log) Number of establishments industry 1 (2)* is the log of the average number of firms in the first (second) industry in the corresponding industry pair. *Share of total manufacturing VA industry 1 (2)* is the average share of the first (second) industry pair on total manufacturing value added. The dependent variable is the correlation of growth rates of real value added between industry-pairs in different countries. The results reported correspond to those obtained in our high quality sample of 39 countries (column (1)), dropping the countries where the corresponding measures of trade credit were below the 5th and above the 95th percentile levels observed in our main sample (column (2)), and dropping those industries where the corresponding measures of the generic credit chain distances were below the 5th and above the 95th percentile levels observed in our set of industry pairs (column (3)). The coefficients reported in Column (4) were obtained in a robust regression. All averages mentioned above were computed over the period 1980-2000. All regressions include country and industry pair fixed effects. Standard errors are robust to heteroskedasticity. * = Significant at 10 percent level, ** = Significant at 5 percent level, *** = Significant at 1 percent level.

Table 10. Different measures of correlations and distances

	Using HP filter	Transformed Correlation	Robust correlation	Using Country level Information	Using UK input-output data
	(1)	(2)	(3)	(4)	(5)
Credit Chain Distance (Payables Financing) $^{(\alpha)}$	1.745***	4.592***	1.722***	--	--
	(0.368)	(0.805)	(0.393)		
Credit Chain Distance Country Basis $^{(\alpha)}$	--	--	--	1.871***	--
				(0.306)	
Credit Chain Distance (using UK data) $^{(\alpha)}$	--	--	--	--	1.618***
					(0.293)
(log) Number of establishments industry 1	0.023***	0.057***	0.023***	0.024***	0.024***
	(0.005)	(0.009)	(0.004)	(0.004)	(0.004)
(log) Number of establishments industry 2	0.001	0.049***	0.030***	0.025***	0.025***
	(0.006)	(0.011)	(0.005)	(0.004)	(0.004)
Share of total manufacturing VA industry 1	-0.230*	-0.627***	-0.327***	-0.230**	-0.232**
	(0.122)	(0.226)	(0.111)	(0.098)	(0.098)
Share of total manufacturing VA industry 2	-0.074	-1.403***	-0.945***	-0.666***	-0.671***
	(0.126)	(0.243)	(0.117)	(0.104)	(0.104)
Constant	0.455***	-0.190**	-0.079*	-0.085**	-0.088**
	(0.061)	(0.095)	(0.044)	(0.040)	(0.040)
Observations	10194	12651	12683	12683	12683
R-squared	0.32	0.38	0.33	0.35	0.35
Industry pair FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes

Credit chain distance is the measures of the intensity of use of trade credit in the chain linking two industries based on the *Payables Financing* ratio. *(log) Number of establishments industry 1 (2)* is the log of the average number of firms in the first (second) industry in the corresponding industry pair. *Share of total manufacturing VA industry 1 (2)* is the average share of the first (second) industry pair on total manufacturing value added. In Columns (1) to (3) the dependent variables are the correlation of the series of real value added detrended using the Hodrik-Prescott filter, the Otto et al. (2001) transformation of the correlation of the growth rate of real value, and a robust measure of the correlation of real value added growth between the industries in a pair, respectively. Columns (4) and (5) present results obtained using a measure of credit chain distance that exploits the existing information on industry level use of trade credit across countries and a measure based on the UK input-output matrices, respectively. All averages mentioned above were computed over the period 1980-2000. All regressions include country and industry pair fixed effects. Standard errors are robust to heteroskedasticity. * = Significant at 10 percent level, ** = Significant at 5 percent level, *** = Significant at 1 percent level.

Table 11. Other dimensions of similarity across industry pairs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Chain Distance (Payables Financing) (α)	2.177***	2.037***	2.036***	1.782***	2.020***	2.057***	2.063***	1.900***
	(0.345)	(0.337)	(0.328)	(0.372)	(0.326)	(0.327)	(0.328)	(0.338)
BUY distance X Payables Financing	-0.723	--	--	--	--	--	--	--
	(0.484)	--	--	--	--	--	--	--
SELL distance X Payables Financing	0.563**	--	--	--	--	--	--	--
	(0.229)	--	--	--	--	--	--	--
Dist. external finance X Financial Development	--	-0.000	--	--	--	--	--	--
	--	(0.014)	--	--	--	--	--	--
Dist. liquidity needs X Financial Development	--	-0.437***	--	--	--	--	--	--
	--	(0.129)	--	--	--	--	--	--
Dist. capital per employee x Capital per Worker	--	0.001	--	--	--	--	--	--
	--	(0.023)	--	--	--	--	--	--
Dist. Gini intermediary shares X Overall Volatility	--	--	21.047*	--	--	--	--	--
	--	--	(10.763)	--	--	--	--	--
Cost distance X Payables Financing	--	--	--	1.950	--	--	--	--
	--	--	--	(1.244)	--	--	--	--
Cost Based Credit Chain (Payables Financing)	--	--	--	--	2.854***	--	--	--
	--	--	--	--	(0.828)	--	--	--
Cost Based Credit Chain (Receivables Financing)	--	--	--	--	--	0.139	--	--
	--	--	--	--	--	(0.864)	--	--
Correlation from differences in shocks volatilities	--	--	--	--	--	--	0.006	--
	--	--	--	--	--	--	(0.013)	--
Generic Credit Chain Dist. X Overall Volatility	--	--	--	--	--	--	--	-2.408*
	--	--	--	--	--	--	--	(1.447)
Observations	12683	10241	12683	12683	12683	12683	12683	12683
R-squared	0.35	0.34	0.35	0.35	0.35	0.35	0.35	0.35
Number of establishments both industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share of total manufacturing VA both industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

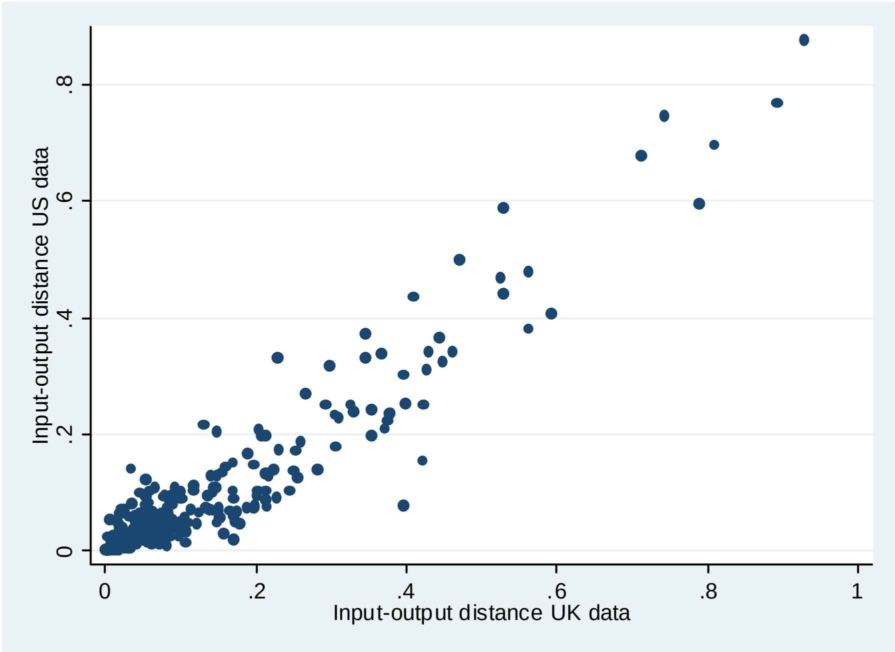
The dependent variable is the correlation of growth rates of real value added between industry-pairs in different countries. *Credit chain distance* is the measures of the intensity of use of trade credit in the chain linking two industries based on *Payable Financing*. *BUY (SELL) distance X Payables Financing* are the interaction between Conley and Dupor (2003)'s measure of similarity between two industries in terms of suppliers (customers) and a country's median level of payables to cost of goods sold. *Dist. external finance X Financial Development* is the interaction of the absolute value of an industry pair's difference in external financial requirements (Rajan and Zingales, 1998) and a country's level of *Financial Development* measured as the (log) average ratio of Private Credit to GDP. *Dist. liquidity needs X Financial Development, Dist. capital per employee X Capital per Worker,* and *Dist. Gini intermediary shares X Overall Volatility* are computed analogously. *Cost Distance x Payables Financing* is the interaction between Shea (2002)'s measure of an industry pair's strength of forward linkages and a country's payables financing. *Cost based Credit Chain (Payables financing)* and *Cost based Credit Chain (Receivables financing)* are the measures of credit chains built using Shea (2002)'s *COST* matrix and payables and receivables financing as measures of trade credit use, respectively. *Correlation from differences in shocks volatility* is the contribution of differences in the volatility of shocks to various industries to an industry pair correlation. *Generic Credit Chain Dist. X Overall Volatility* is the interaction of an industry pair's generic credit chain distance and a country's standard deviation of real GDP per capita growth. All averages and standard deviations mentioned above are computed over the period 1980-2000. All regressions include country fixed effects and control for the average number of firms and share of total manufacturing value added of each industry in the pair. Standard errors are robust and clustered at the industry-pair level. * = Significant at 10 percent level, ** = Significant at 5 percent level, *** = Significant at 1 percent level.

Table 12. Alternative Explanations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Credit Chain Distance (Payables Financing) (α)	1.924***	1.886***	2.272***	2.357***	1.867***	2.034***	--
	(0.332)	(0.341)	(0.330)	(0.334)	(0.331)	(0.328)	--
Generic Credit Chain Distance X (log) GDP per capita	0.070***	0.064***	--	--	--	--	--
	(0.023)	(0.024)	--	--	--	--	--
Generic Credit Chain Distance X Growth Volatility	--	-0.732	--	--	--	--	--
	--	(1.544)	--	--	--	--	--
Credit Chain Distance X Financial Development	--	--	0.810***	--	--	--	--
	--	--	(0.210)	--	--	--	--
Credit Chain Distance X Short term debt to Payables	--	--	--	-0.603***	--	--	--
	--	--	--	(0.154)	--	--	--
Generic Credit Chain Distance X Trade Openness	--	--	--	--	-0.086***	--	--
	--	--	--	--	(0.030)	--	--
Direct Credit Chain Distance (Payables Financing)	--	--	--	--	--	7.427**	--
	--	--	--	--	--	(2.988)	--
Credit Chain Distance (Common use)	--	--	--	--	--	--	2.294***
	--	--	--	--	--	--	(0.345)
Credit Chain Distance (Differential use)	--	--	--	--	--	--	-2.697
	--	--	--	--	--	--	(2.465)
Observations	12683	12683	12683	12683	12683	12683	12683
R-squared	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Number of establishments both industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share of total manufacturing VA both industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

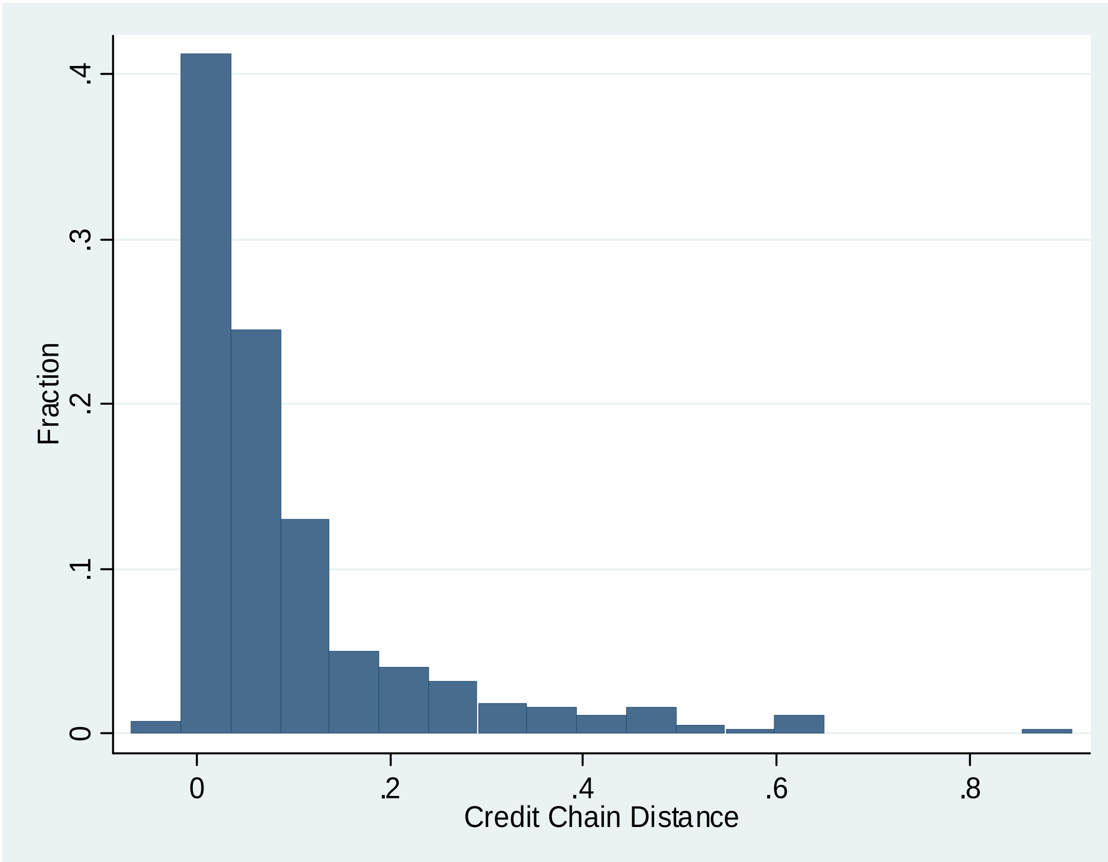
Credit chain distance (Payables Financing) is the measures of the intensity of use of trade credit in the chain linking two industries based on the ratio of *payables to cost of goods sold. Generic Credit Chain Distance x (log) GDP per capita, Generic Credit Chain Distance x Growth Volatility,* and *Generic Credit Chain Distance X Trade Openness* are the interactions between an industry pair's generic credit chain distance and a country's (log) GDP per capita, standard deviation of the growth of real GDP per capita, and the log average ratio of total exports to GDP. *Credit Chain Distance X Financial Development* and *Credit Chain Distance X Short-term debt to payables* are the interactions between these two variables. *Direct Credit Chain Distance* is the credit chain distance computed considering only the direct linkages among industries. *Credit Chain Distance (Common Use)* is the distance computed using the average payable financing of all industries, and *Credit Chain Distance (differential use)* is the distance computed using the industries deviations from that average only. These two distances add to the baseline measure of credit chain distance. All averages mentioned above are computed over the period 1980-2000. All regressions include country fixed effects and control for the average number of firms and share of total manufacturing value added of each industry in the pair. Standard errors are robust to heteroskedasticity. * = Significant at 10 percent level, ** = Significant at 5 percent level, *** = Significant at 1 percent level.

Figure 1. Input-Output Distances US and UK



The figure plots the input-output distances of the 378 industry pairs formed by the combination of our 28 3-digit ISIC manufacturing industries computed using data from UK (x-axis) and US (y-axis) input-output matrices.

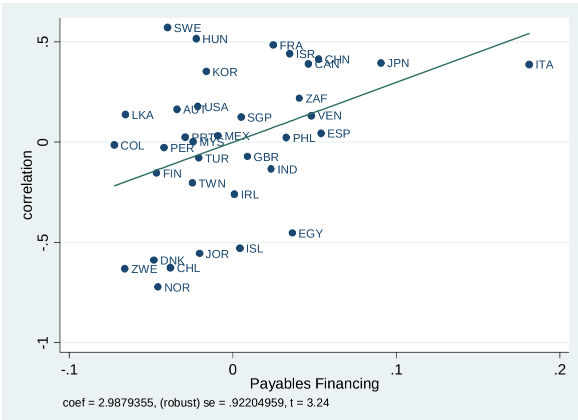
Figure 2. Distribution of Credit-Chain Distances across industries



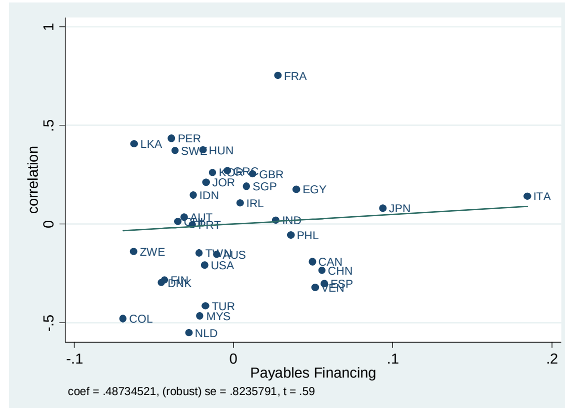
The figure shows the histogram of generic credit-chain distances across (non-repeated) industry pairs excluding the pairs corresponding to an industry and itself. The y-axis displays the fraction of the population in each of the bins depicted in the x-axis.

Figure 3. Differential effect of trade credit use in sectors with small and large distances

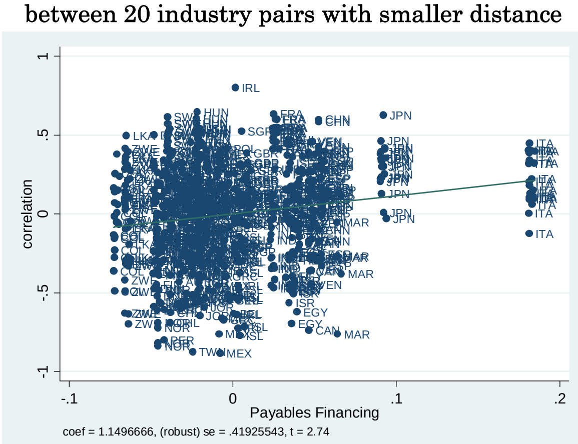
Panel A. Payables financing and the correlation between Iron and Steel and Transport Equipment industries (small distance)



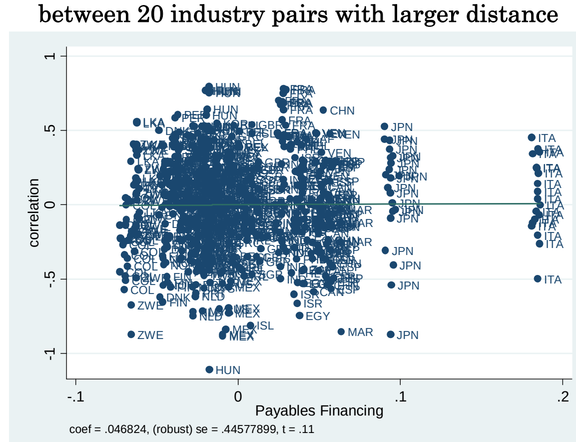
Panel B. Payables financing and the correlation between Tobacco and Footwear industries (large distance)



Panel C. Payables financing and the correlation between 20 industry pairs with smaller distance



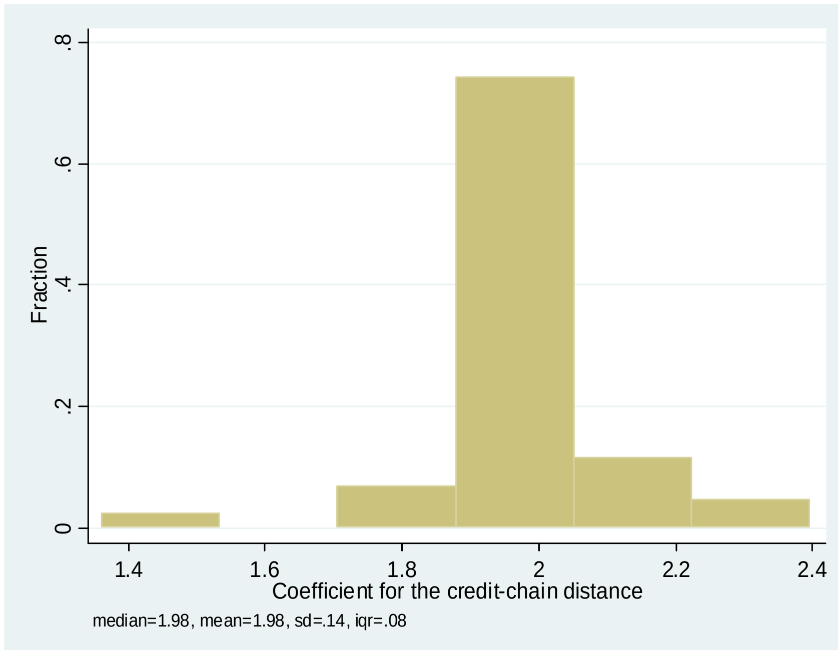
Panel C. Payables financing and the correlation between 20 industry pairs with larger distance



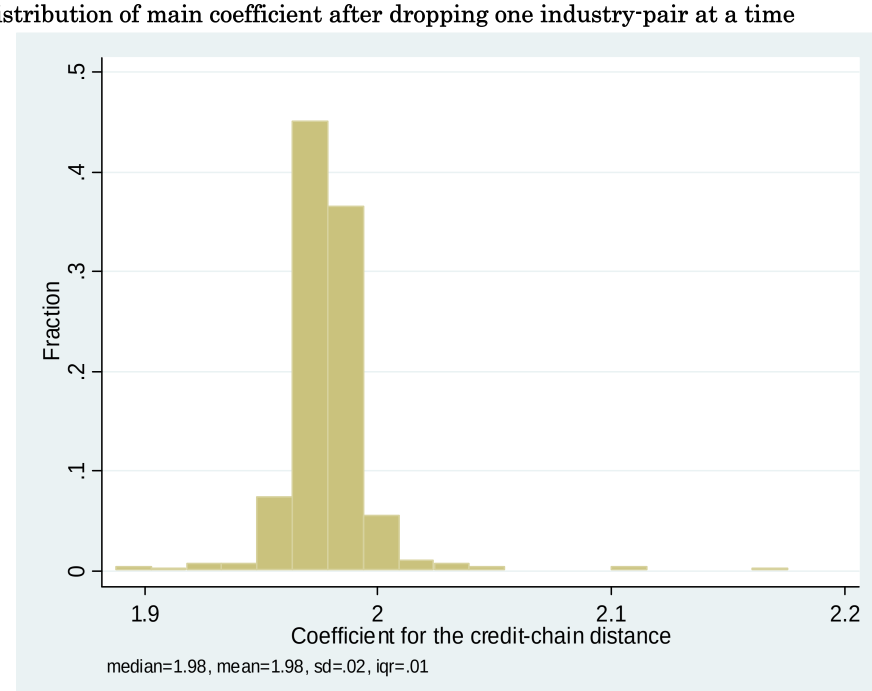
The figures in Panels A to D show the relation between the median level of *Payables Financing* among manufacturing firms and the correlation of real value added growth in the industry pair formed by the Iron and Steel and Fabricated Metal Product industries, the industry pair formed by the Tobacco and Footwear industries, the 20 industry pairs that are closer in credit chain distance, and the 20 industry pairs that are farther in credit chain distance, respectively. Each figure reports the coefficient (coef) of an OLS regression between the measures of correlation and payables financing (plus an industry-pair fixed effect in panes C and D) for the industry pairs considered in each case. The reported standard errors and t-statistics (se and t) are clustered at the country level.

Figure 4. Distribution of main coefficient after dropping countries and industries

Panel A. Distribution of main coefficient after dropping one country at a time



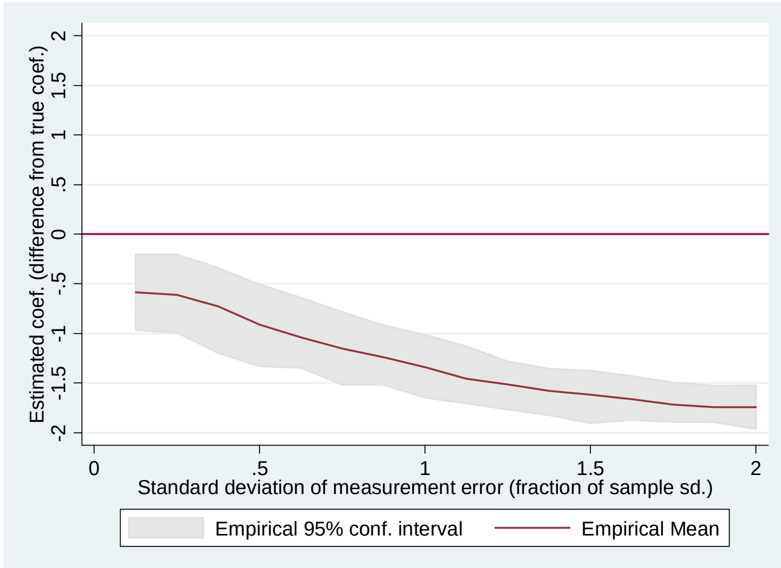
Panel B. Distribution of main coefficient after dropping one industry-pair at a time



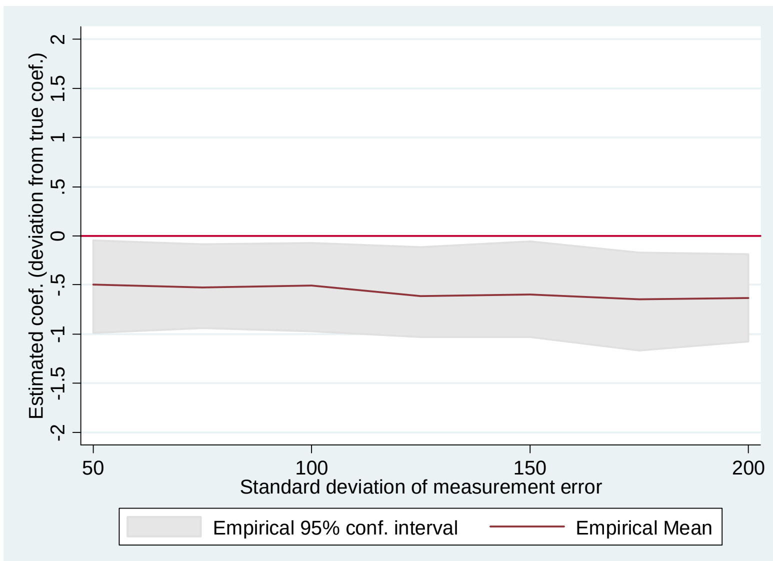
The figure in Panel A shows the distribution of the OLS coefficient of credit-chain distance obtained after dropping one country of the sample at a time. Panel B shows a similar histogram obtained after dropping one industry-pair at a time

Figure A1. Effect of measurement error on the coefficient estimated for the effect of credit-chain distance on correlations

Panel A. Measurement error on the Payables Financing ratio



Panel B. Measurement error associated with the use of a common measure of Input-Output Linkages



The two panels of the figure display the empirical distribution of the difference between the estimated and true coefficient for the effect of credit-chain distance on sectoral correlations (y-axis) obtained from a series of Montecarlo simulations for different variances of the measurement error on the payables financing (Panel A), and Input-Output Linkages (Panel B) (x-axis). In each panel, the line represents the mean estimated coefficient and the shaded area the empirical 95 percent distribution. The value of the true coefficient is all simulations is 2.